Presentation on GPT

How does Chat GPT actually Work?

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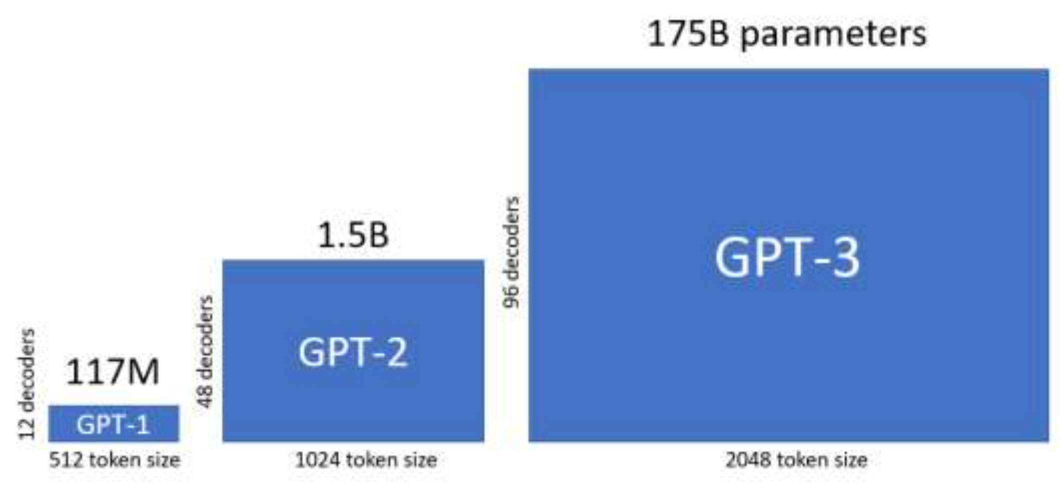
01

What is ChatGPT?

Chat GPT

- ChatGPT is a conversational AI developed by OpenAI.
- Based on the GPT (Generative Pre-trained Transformer) architecture.
- Designed to engage in natural language conversations with users, providing responses that are contextually relevant and coherent.
- ChatGPT has been trained on a vast amount of text data from the internet, allowing it to generate human-like responses to a wide range of prompts and questions



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History that led to ChatGPT

HOW IT ALL STARTED?

GPT-1 (2018-2019):

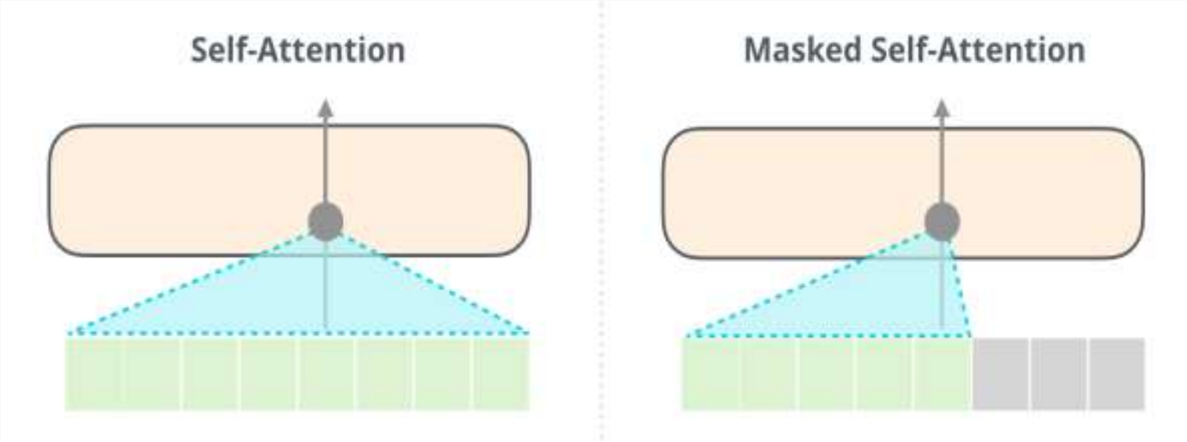
- OpenAI introduced GPT-1 [1] in June 2018, marking a significant advancement in natural language processing. It utilized a transformer architecture and was trained on a vast corpus of internet text.

Release of GPT-2 (2019):

- OpenAI released the full version of GPT-2 [2] in November 2019.
- A staged release plan was implemented to address concerns about potential misuse.
- Researchers and developers began exploring various applications of GPT-2, including text generation, chatbots, content creation, and language translation.

ChatGPT-3, 3.5, 4:

- Following the release of GPT-3 [3] , OpenAI and other research teams continued to advance and refine transformer-based models for natural language processing.
- These advancements also extended to incorporating capabilities for image and voice inputs.



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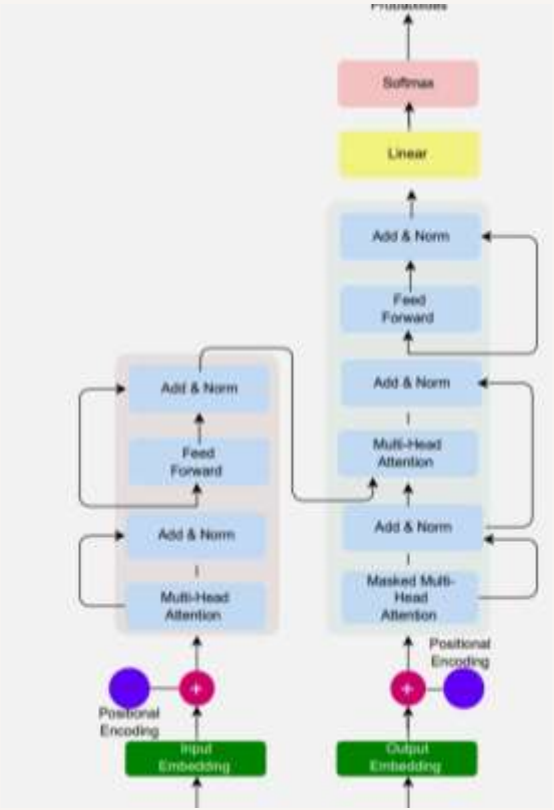
Working of GPT

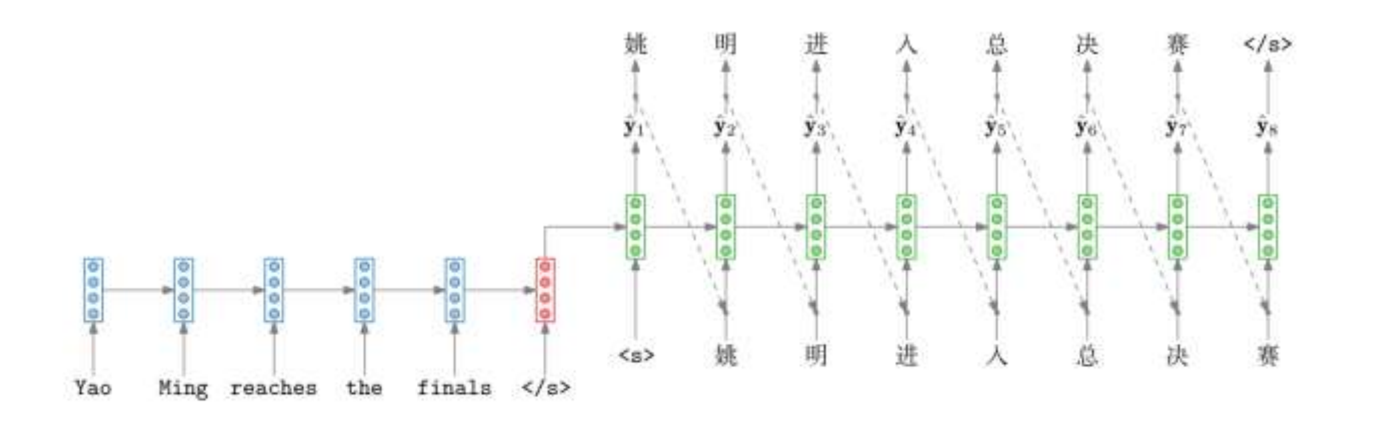
Transformer Architecture

- Even though we don’t know exact source code for the ChatGPT., we do know how it works.
- Most of the heavy things are done through the Transformer model.
- This is first proposed in the paper “Attention is all you need” [4].
- Let us dive deep into this monstrosity and peel block by block on how it works.



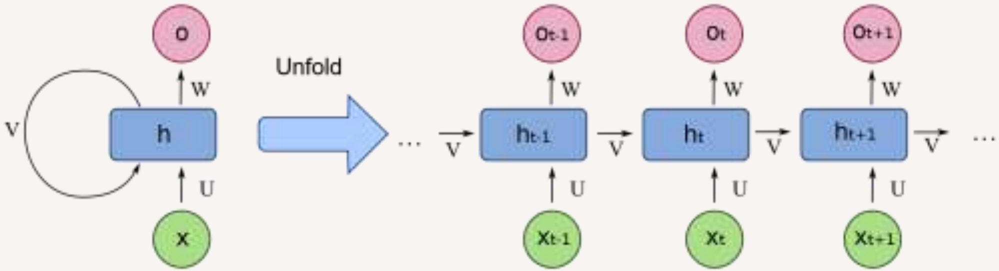
Encoder & Decoder Model

- To understand from the start lets refresh our minds on the previous ways to generate text, predictions and machine translation.
- We will not talk about the vanilla RNN encoder decoder model in detail. but let us view this in a higher picture.



E&D model

- Encoder contains RNN network that takes the input in a sequence and tokenizes the sentence
- It only contains one block and connects to itself.
- But the time steps can be unfolded to get a better visualization.



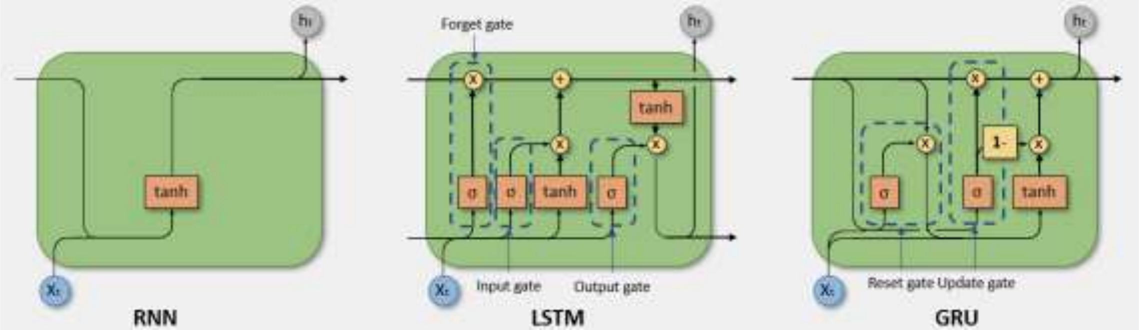
- All we are trying to do is to **minimize the negative log likelihood** to get better predictions

Issues

- The issue arises at the context vector (latent space), where all input sequence information is condensed into one large vector space and sent to the decoder.

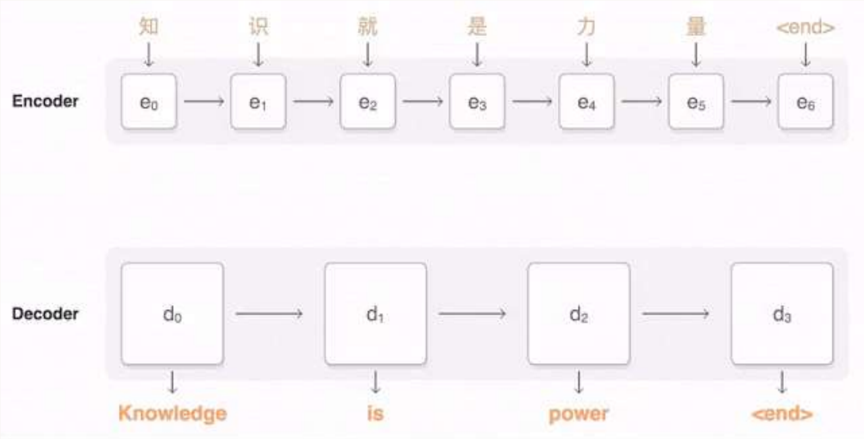
- The expectation is for the model to *retain* this information until the decoding stage, but it *often fails* to do so.

- Various versions of RNN, such as LSTM and GRU, have been developed to address this issue and enable the model to preserve information until the very end.



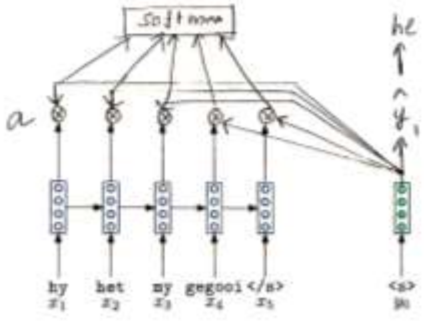
Attention (Encoding)

- Attention is proposed in 2015 (Bengio et. al.)
- Attention focuses on looking all the inputs at each time step.
- In this way we can see the ground truth and make a higher prediction probability.



Forward pass:

the output of $y_0 = (\hat{y}_1)$ can be high for first word, as it has more weightage.



here x_n, y_n are Tensors,

$a_n = (x_n \otimes y_n) \ \exists \ x = 1 \cdots n, \ y = 1 \cdots n$

[The dot product o/p can be $\boxed{-\alpha \text{ to } \alpha}$]

The output of softmax be $\alpha_1, \alpha_2 \cdots \alpha_n$

If α is high, the present decoder Time step is really looking at that time point.

- Encoder hidden states:

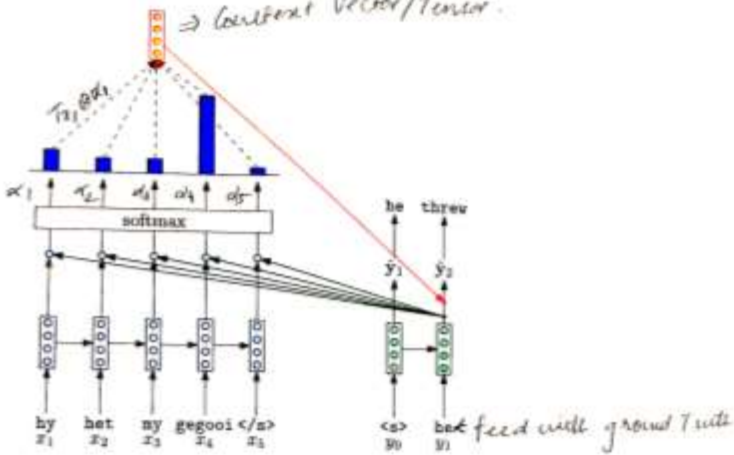
$$\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_N \in \mathbb{R}^D$$

- Decoder hidden state at time step t:

$$\mathbf{s}_t \in \mathbb{R}^D$$

- Attention score for encoder hidden state $\mathbf{h}_n$:

$$a(\mathbf{s}_t, \mathbf{h}_n) = \mathbf{s}_t^\top \mathbf{h}_n \in \mathbb{R}$$



- Take the First hidden Representation, scale it to alpha $T_{x_1} \otimes \alpha_1$ ||ly others $T_{x_2} \otimes \alpha_2 \cdots T_n \otimes \alpha_n$
- Sum it $\boxed{\sum_{n=1}^{K} T_{x_n} \otimes \alpha_n}$

The O/p of this is a One Giant Tensor '$\underline{C}$'.
This '$\underline{C}$' is "context vector" (like bottle neck) vector average of all Time steps for curnt decoder Time step.

- Attention weight for encoder hidden state $\mathbf{h}_n$:

$$\alpha(\mathbf{s}_t, \mathbf{h}_n) = \mathrm{softmax}_n\left(a(\mathbf{s}_t, \mathbf{h}_n)\right) = \frac{\exp\{a(\mathbf{s}_t, \mathbf{h}_n)\}}{\sum_{j=1}^{N} \exp\{a(\mathbf{s}_t, \mathbf{h}_j)\}} \in [0, 1]$$

- Context vector at decoder time step t:

$$\mathbf{c}_t = \sum_{n=1}^{N} \alpha(\mathbf{s}_t, \mathbf{h}_n)\mathbf{h}_n \in \mathbb{R}^D$$

- Concatenate:

$$\left[\mathbf{c}_t; \mathbf{s}_t\right] \in \mathbb{R}^{2D}$$

and continue as in the non-attention decoding case, e.g.

$$\hat{\mathbf{y}}_t = \mathrm{softmax}\left(\mathbf{W}_{ho}\left[\mathbf{c}_t; \mathbf{s}_t\right] + \mathbf{b}_o\right)$$

Cont.

- Attention is calculated at each hidden representation and projected onto each input layer, resulting in soft probabilities.

- These probabilities provide high and low weights during training, aiding the machine in understanding what to predict.

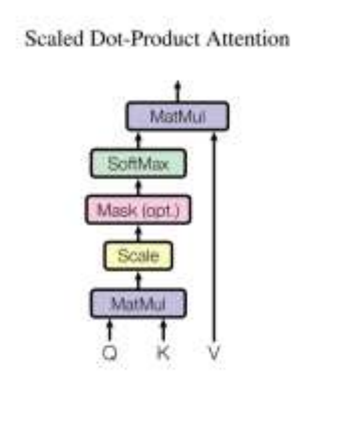
- All context vectors at each time stamp are concatenated into the hidden representation at that time frame to generate predictions or translations.

- This approach leads to significant improvements, as it enables GPU performance by **parallelizing data calculations** similar to feedforward networks, without relying on output data.

- Consequently, large datasets can be efficiently represented in vector forms, facilitating parallelized calculations.

Attention with keys, Queries, Values

- In the paper Attention is all you need., Vaswani et.al has proposed self-attention.



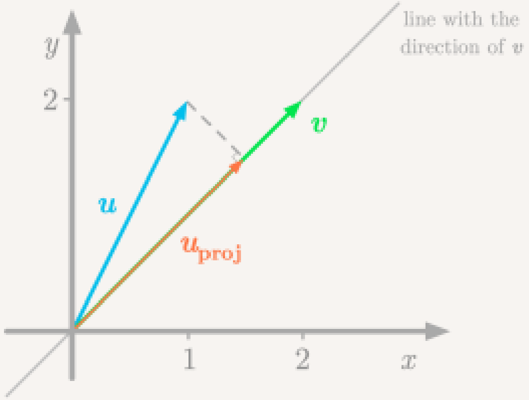
- Queries – Vector from which attention is looking
- Keys – vector at which query looks to compute weights
- Values – Their weighted sum is attention output

Contd.

- Mathematically, represented as :

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

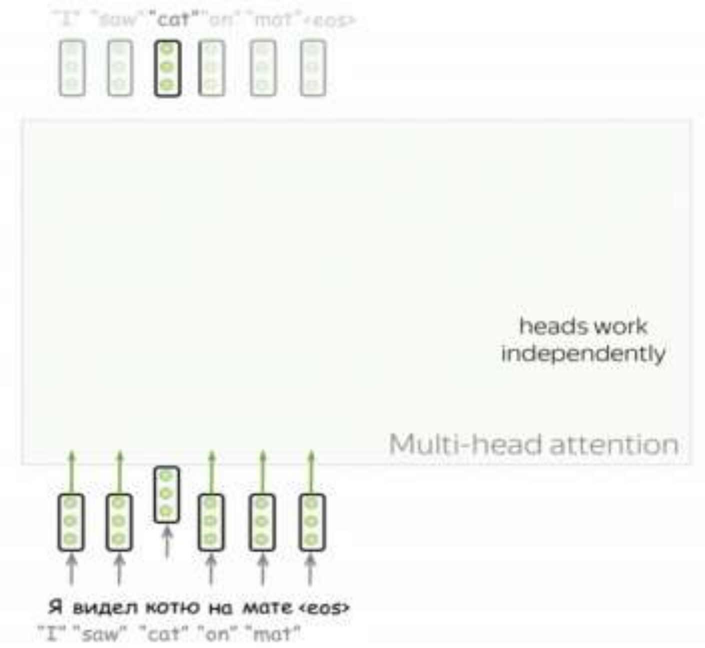
- We do scale dot product for keeping all the vector space/span in same dimension.
- This way we get similarity matrix to high accuracy.



$$u \cdot v = ||u_{\text{proj}}||_2 \cdot ||v||_2$$

Multi-head & masked attention

- We have been seeing single Attention layer till now. But, in a sentence, we *might be giving* weights regarding only on certain semantic info or Syntactic info.
- The selection process in these layers is like a black box.
- To understand what the machine picks up, additional layers are added, similar to how CNN adds filters.
- This helps in capturing various features in different filters, bridging the black box gap.
- This is called multi-head attention.



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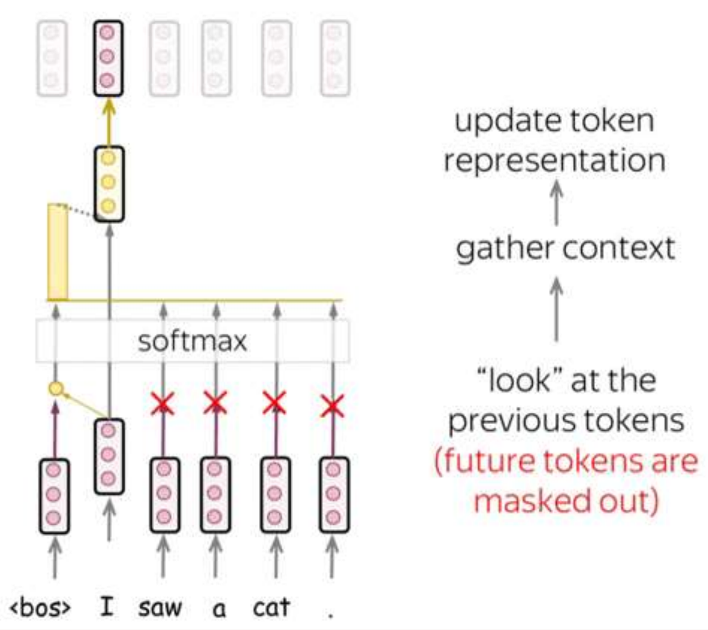
Masked Attn.

- Decoder's self-attention allows tokens to "look at previous tokens" during generation.
- Unlike the encoder, the decoder generates one token at a time.
- Masked self-attention prevents the decoder from **looking ahead** during generation.
- During training, reference translations are used to feed the whole target sentence to the decoder without masks.
- The Transformer's computational efficiency, without recurrence, enables processing all tokens at once, making it *faster for training* compared to recurrent models.



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$$\mathbf{a}_i = \mathrm{softmax}\left(\frac{\mathbf{Q}_i\mathbf{K}_i^\top}{\sqrt{d}} + \mathrm{mask}_i\right)\mathbf{V}_i$$

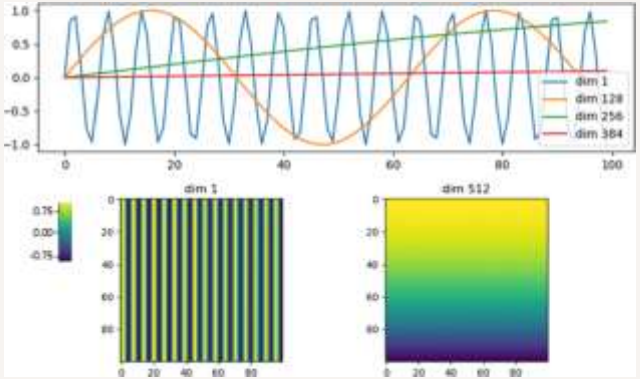
$$\mathrm{mask}_i = \begin{cases} 0 & \text{if } j \leq i \\ -\infty & \text{otherwise} \end{cases}$$

Positional Encoding

- Positional encodings are essential in Transformers to convey the order of input tokens.
- Two sets of embeddings are used: token embeddings and positional embeddings.
- The input representation of a token is the sum of its token embedding and positional embedding.
- Fixed positional encodings are employed in Transformers, utilizing sinusoidal functions.
- The formula for fixed positional encodings is:

$$\text{positional\_encoding}(p, 2i) = \sin\left(\frac{p}{10000^{2i/d_{\text{model}}}}\right)$$

$$\text{positional\_encoding}(p, 2i+1) = \cos\left(\frac{p}{10000^{2i/d_{\text{model}}}}\right)$$



Residual Connections:

- Gradient Flow: Residual connections aid gradient flow by providing shortcut paths, easing training.
- Deep Stacking: They enable the effective stacking of layers, facilitating deeper architectures.
- Training Enhancement: Residual connections mitigate gradient degradation, enhancing training stability.

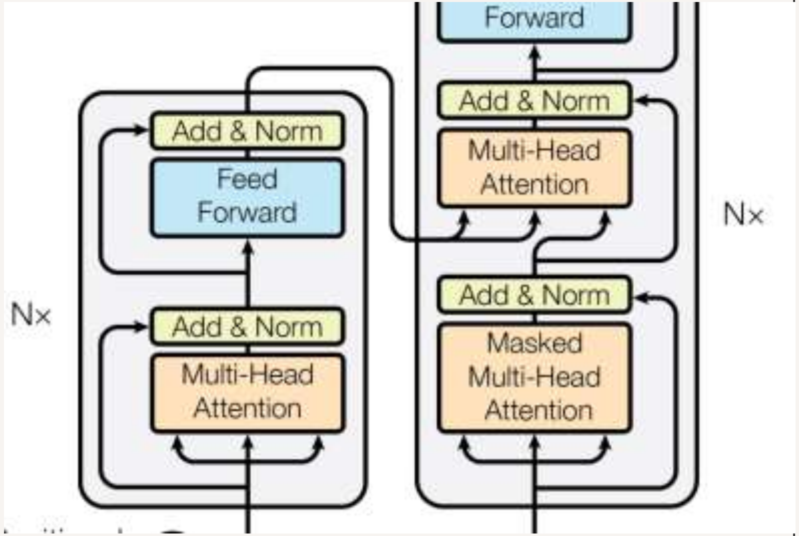
Layer Normalization:

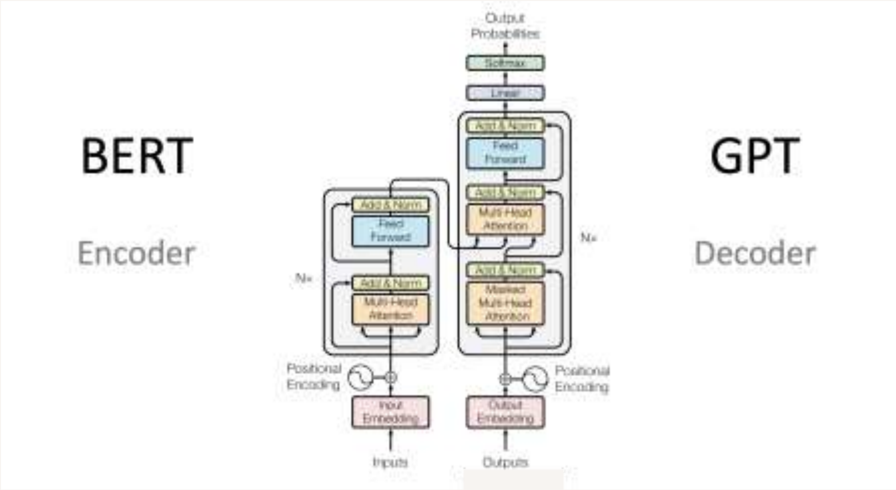
- Batch-wise Regulation: Layer normalization independently normalizes each example in a batch, regulating information flow.
- Stability and Quality: Improves convergence stability and prediction quality by reducing internal covariate shift.
- Trainable Parameters: Includes trainable parameters γ and β for rescaling, enhancing model adaptability.

Cross Attention(Decoding)

- **Keys Extraction**: Extract keys from the encoder outputs for each decoding step.
- **Dot Product**: Perform dot product between the decoder's query and each key.
- **Attention Scores**: Compute attention scores based on the dot products.
- **Weighted Sum**: Calculate a weighted sum of encoder outputs using attention scores.
- **Prediction Output**: Generate prediction output by passing the weighted sum through a linear transformation.

Cross attention





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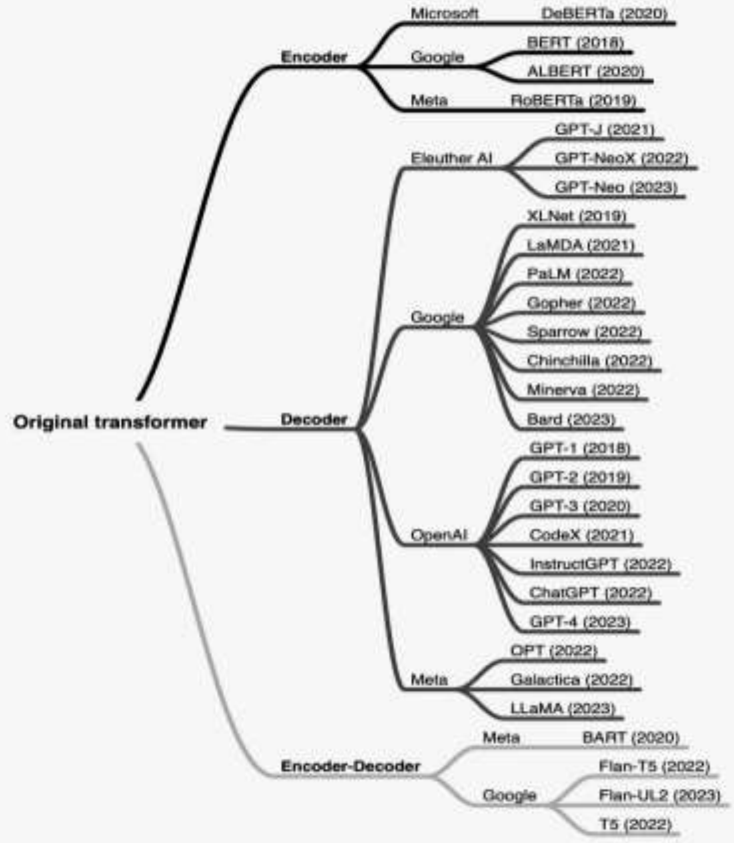
Who Uses GPT?

Encoder only / Decoder only?



ChatGPT

When to use What?

- ChatGPT uses BPE(byte pair encoding) and transformer decoding.

- Encoder-only models focus on processing input sequences, suitable for tasks like classification.
- Decoder-only models generate output sequences based on encoded representations, ideal for text generation tasks.

- ChatGPT and similar models use decoder-only architectures for generating contextually relevant responses in conversations.
- Encoder-decoder architecture is utilized in ChatGPT, where input prompts are first encoded, then decoded to generate responses.

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Limitations of ChatGPT

Limitations

- **Common Sense & Background Knowledge**: Limited understanding of common sense and lacks extensive background knowledge.
- **Emotional Intelligence**: Unable to detect subtle emotional cues or respond appropriately to complex emotions.
- **Performs best with single tasks:** struggles with handling multiple tasks simultaneously.
- **Biases & Limited Knowledge** : Responses may reflect unintentional biases from training data and lack access to recent developments or specialized information, leading to potential accuracy issues.

Conclusion

- GPT operates on transformer architecture with self-attention for text generation.
- ChatGPT, a specialized variant, utilizes a decoder-only model for generating contextually relevant responses in conversations.
- Understanding these models enhances their effectiveness in natural language understanding and generation tasks, improving AI-driven conversational experiences.

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Intuitions are heavily relied on :

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