EE P 500 D: LLMs and ChatGPT || Fine-Tuning LLMs

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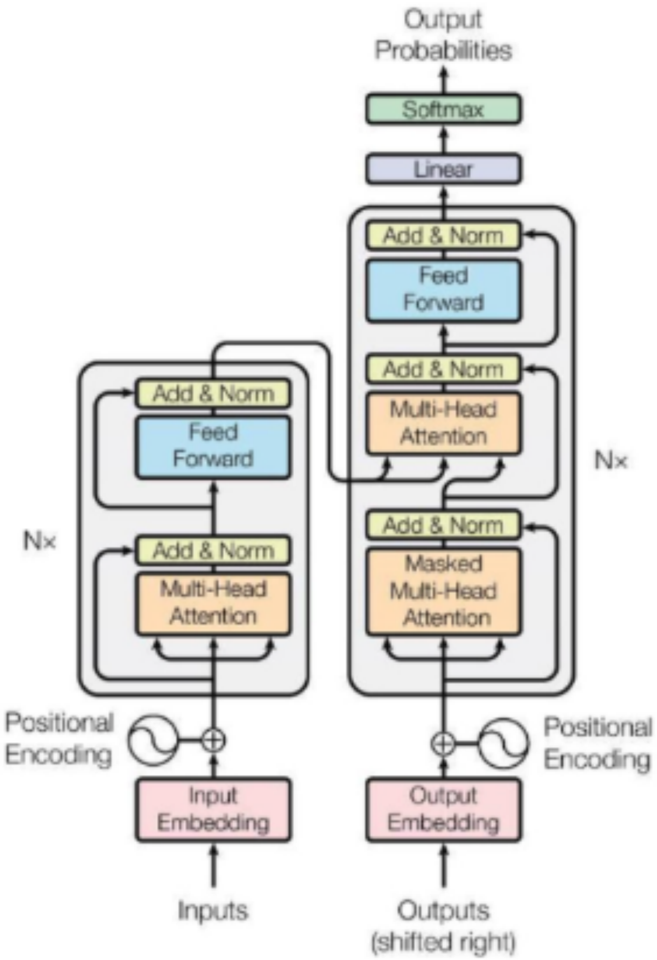
Transformer Archtiecture



Transformers Architecture

Transformer

Reference: Attention is all you need! Vaswani Architecture

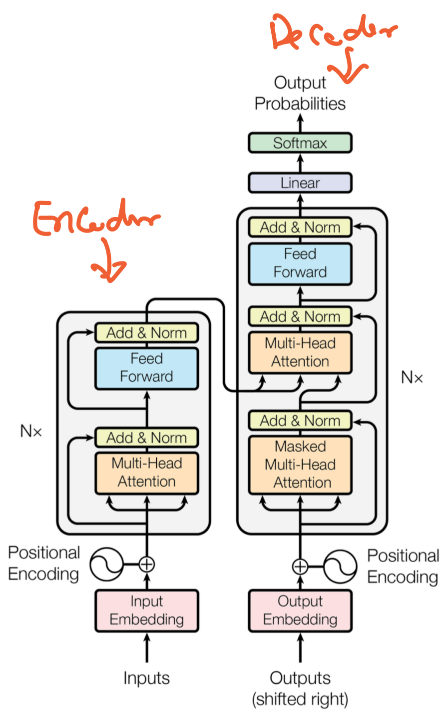


Figure 1: The Transformer - model architecture.

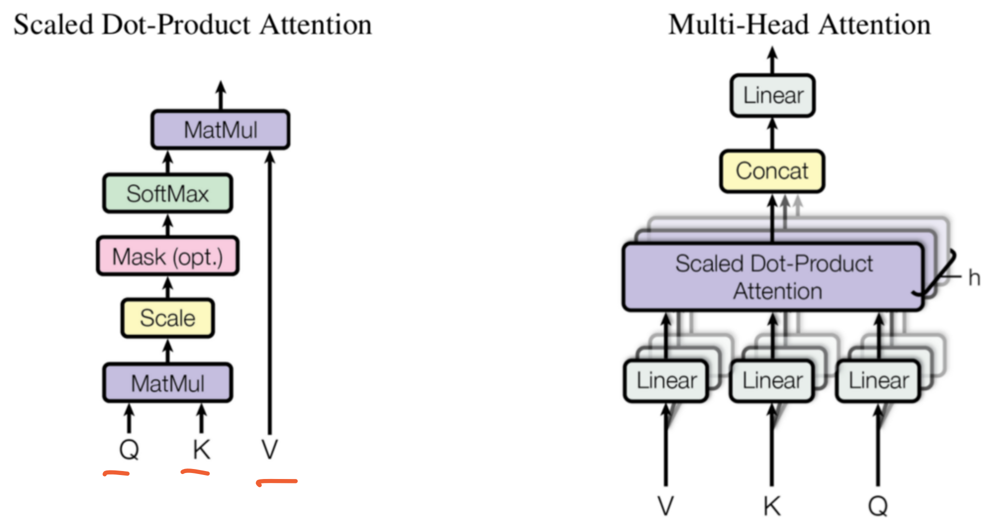


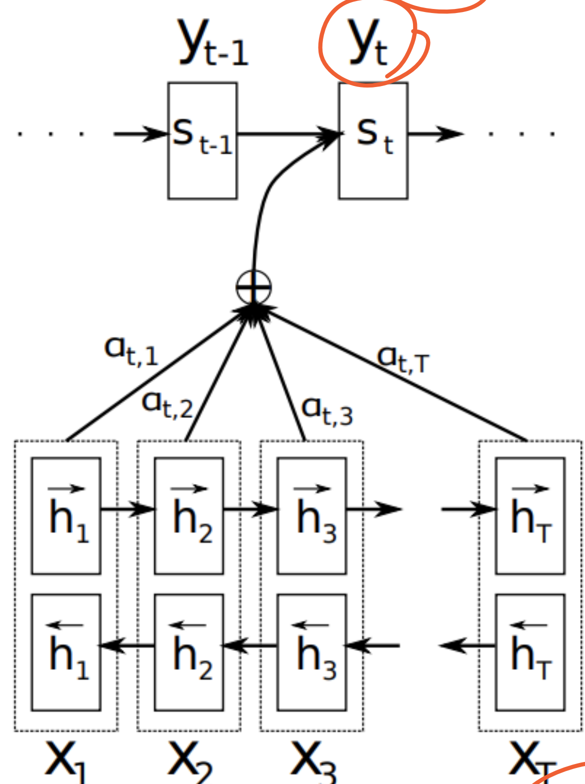
Figure 2: (left) Scaled Dot-Product Attention. (right) Multi-Head Attention consists of several attention layers running in parallel.

First Attention Models

Reference paper

I would like to visit next!

Next Sentence



Encoding

BERT Transformer

Bi-direction

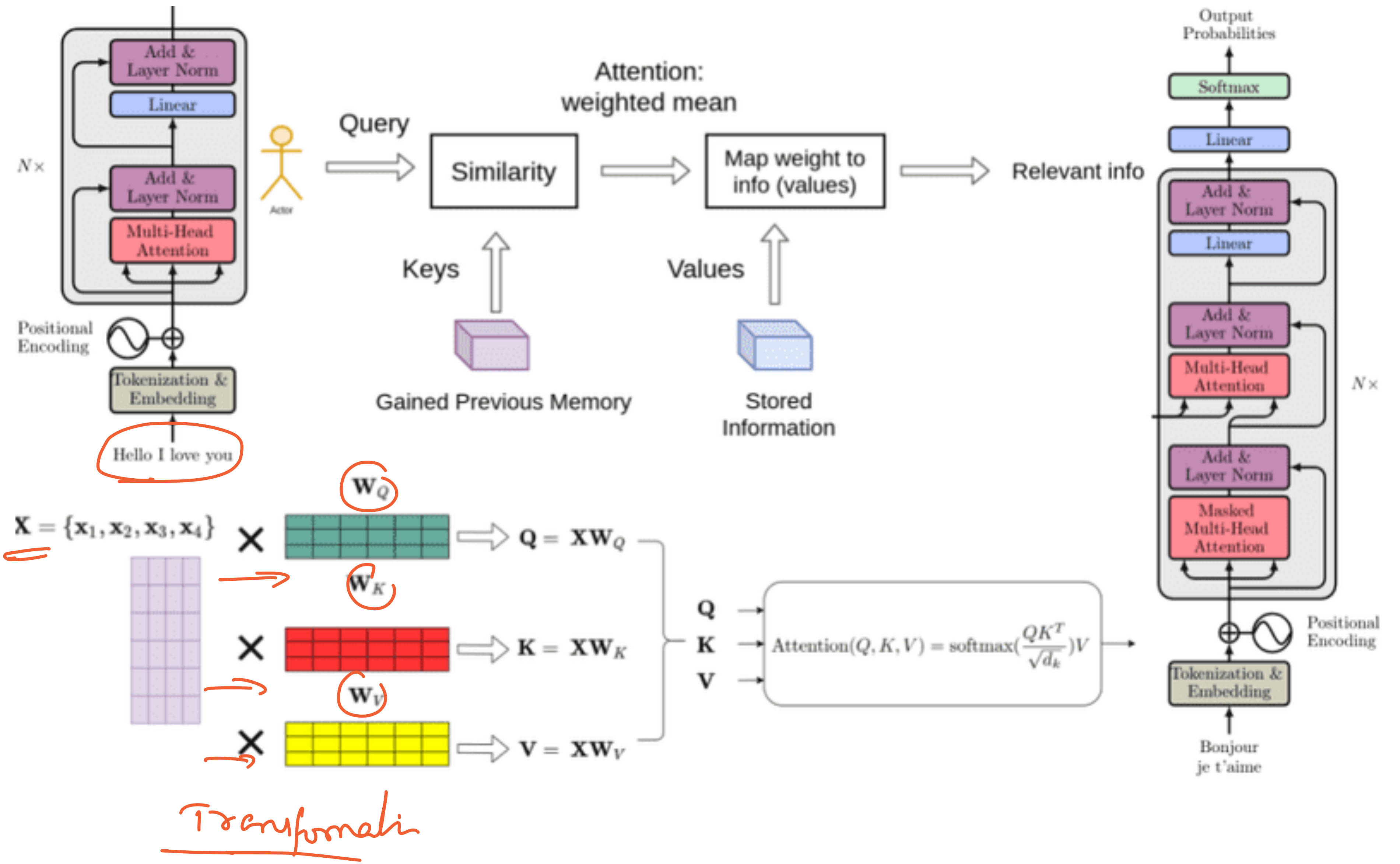
Bi-LSTM

(Pre-Transformer era)!

I am currently in Seattle

Figure 1: The graphical illustration of the proposed model trying to generate the t-th target word y_t given a source sentence $(x_1, x_2, \ldots, x_T)$.

Transformers Architecture

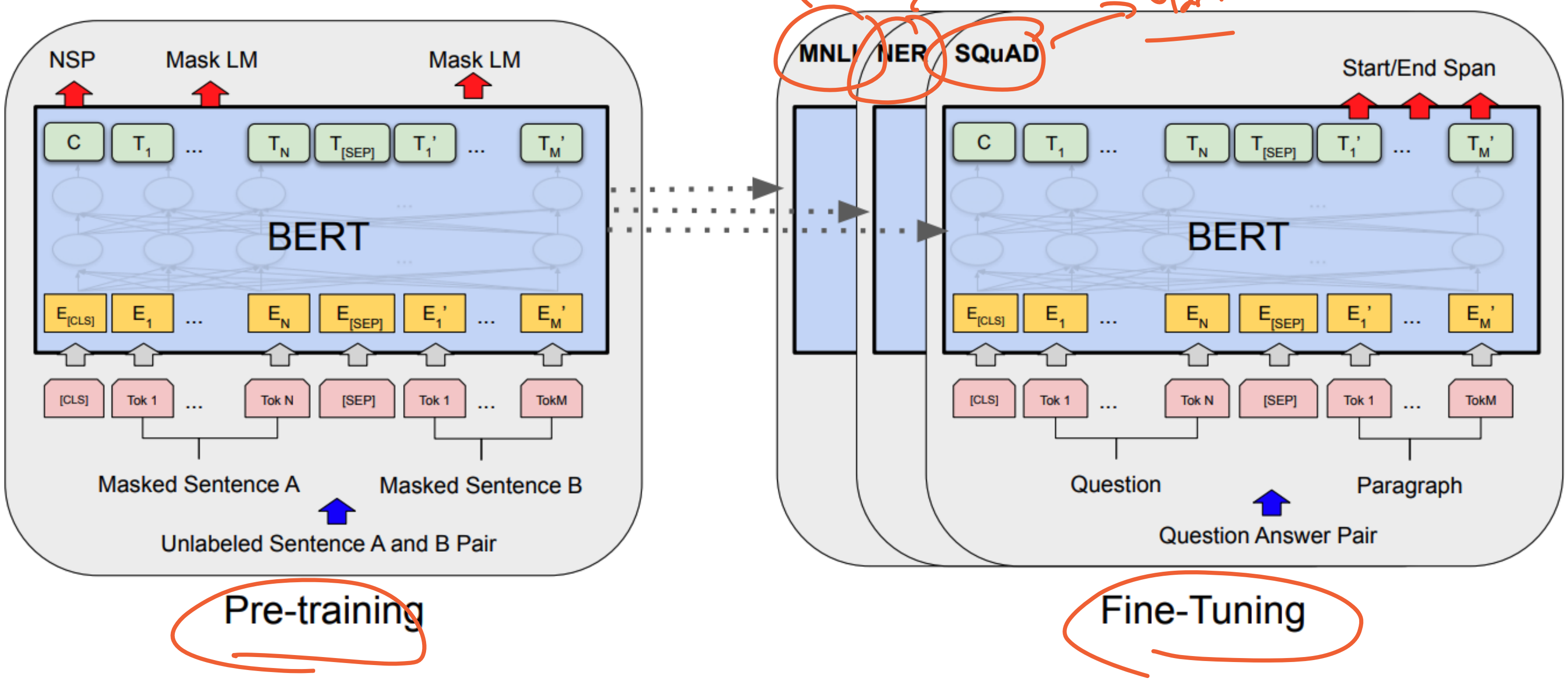


BERT - Bi-directional Encoders from Transformers

Translation

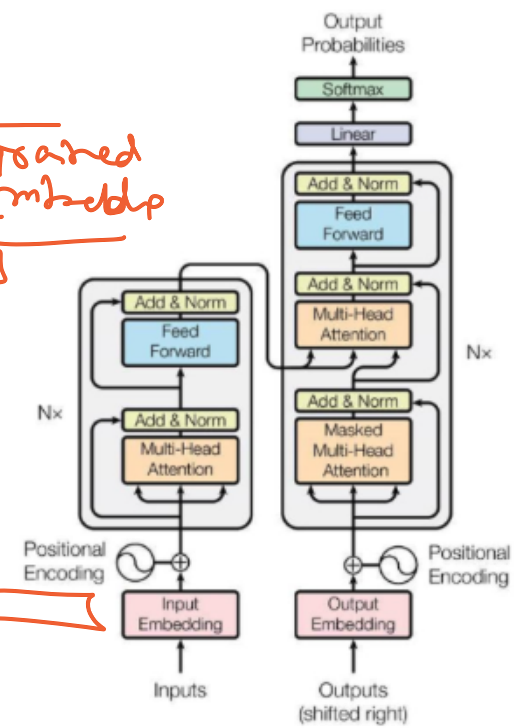
Named Entity Recog

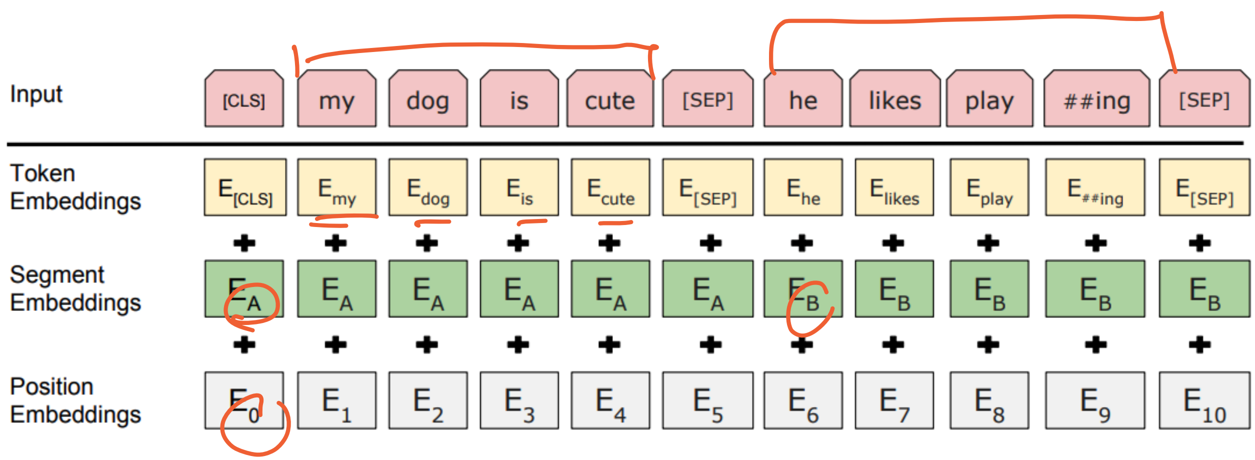
QA



BERT Embeddings

Pre-Trained Embedding





BERT pre-training

Two Tasks

1. **Masked LM Model:** Mask a word in the middle of a sentence and have BERT predict the masked word
2. **Next-sentence prediction:** Predict the next sentence - Use both positive and negative labels. How are these generated?

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ICE: Supervised or Un-supervised?

1. Are the above two tasks supervised or un-supervised?

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Data set!

English Wikipedia and book corpus documents!

BERT - Bi-directional Encoders from Transformers

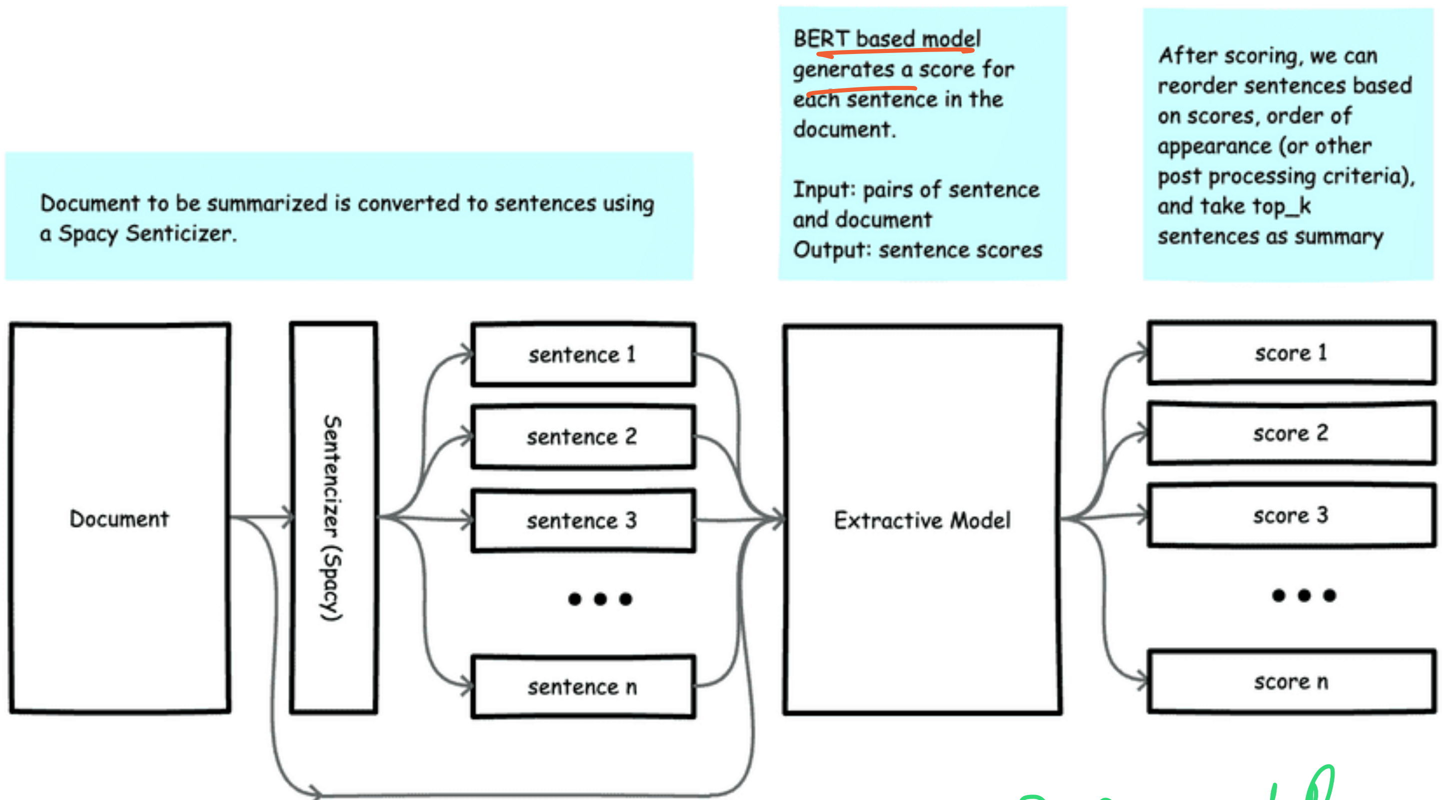
System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

tinyBERT

ROUGE/METEOR Scores for Language Tasks

(Similar to Precision & Recall)

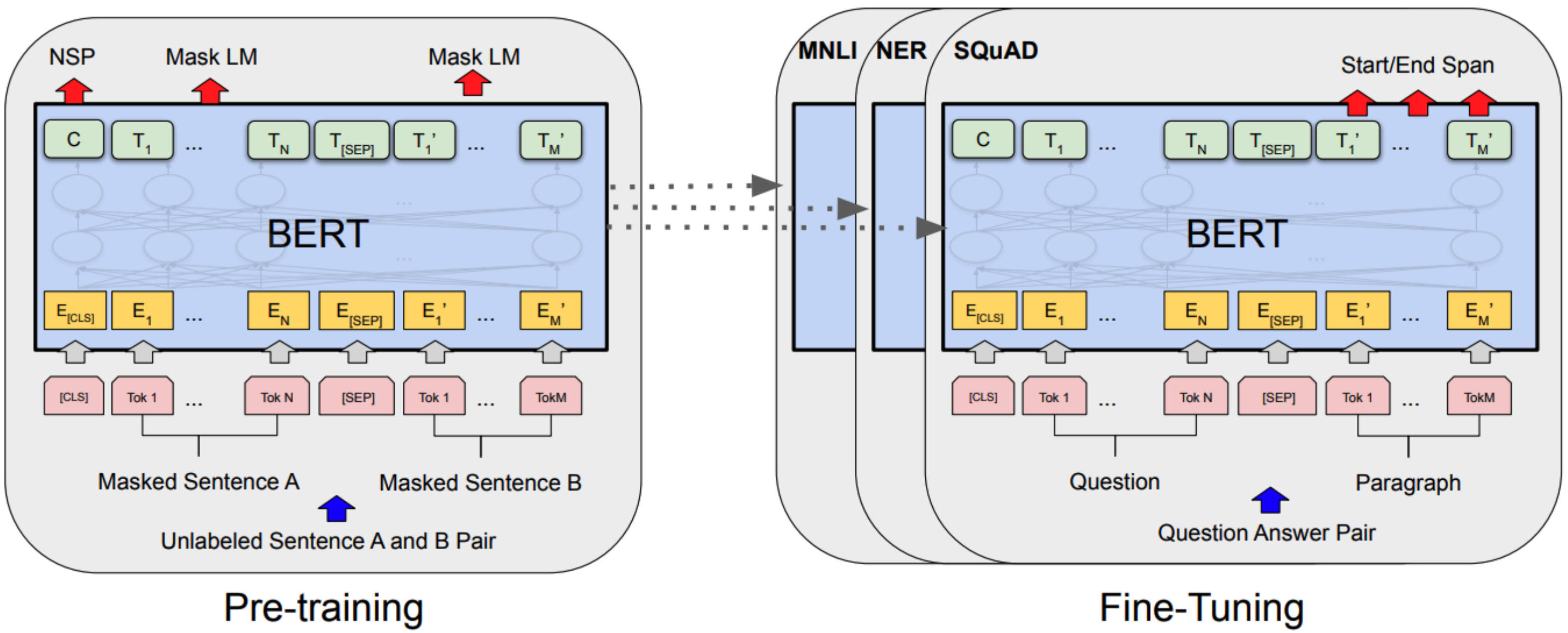
Document Summarization — BERT Based Extractive Model



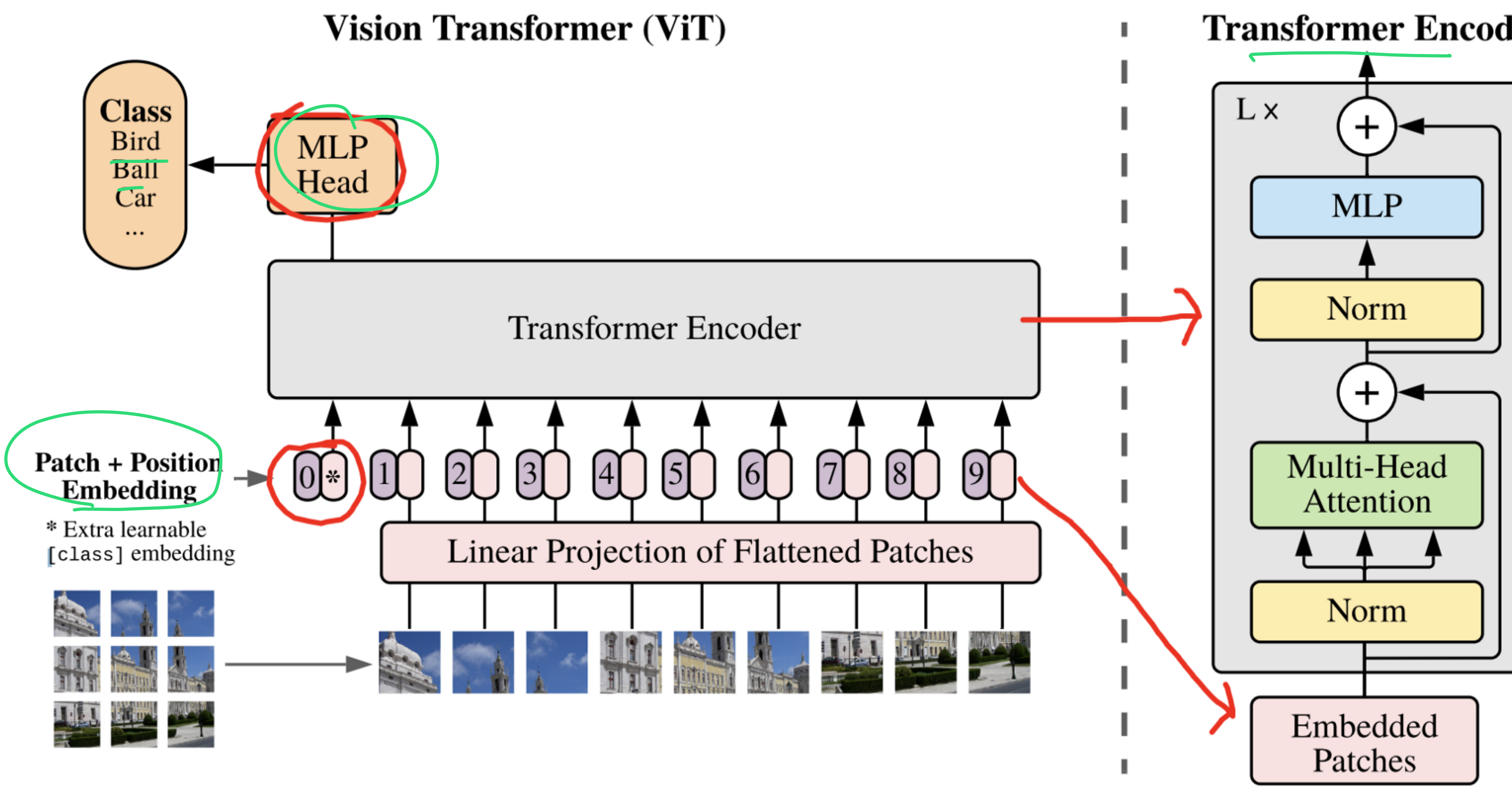
Summarization → Extractive → BERT model

Summarization → Generative → ChatGPT / BART

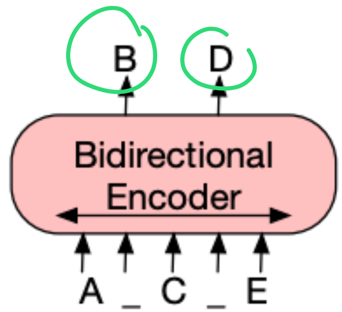
Question Answering — BERT Based Extractive Model



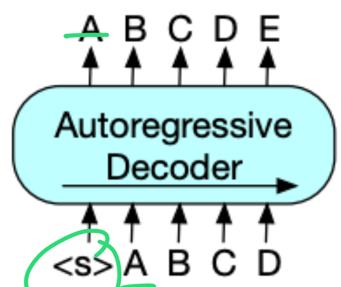
Vision Transformers: Transformers Architecture for Vision



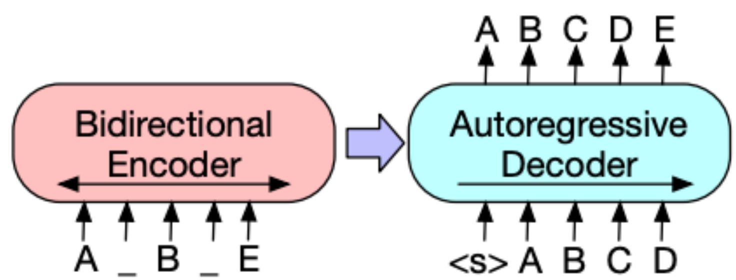
BERT, BART and GPT archs and tasks



(a) BERT: Random tokens are replaced with masks, and the document is encoded bidirectionally. Missing tokens are predicted independently, so BERT cannot easily be used for generation.



(b) GPT: Tokens are predicted auto-regressively, meaning GPT can be used for generation. However words can only condition on leftward context, so it cannot learn bidirectional interactions.

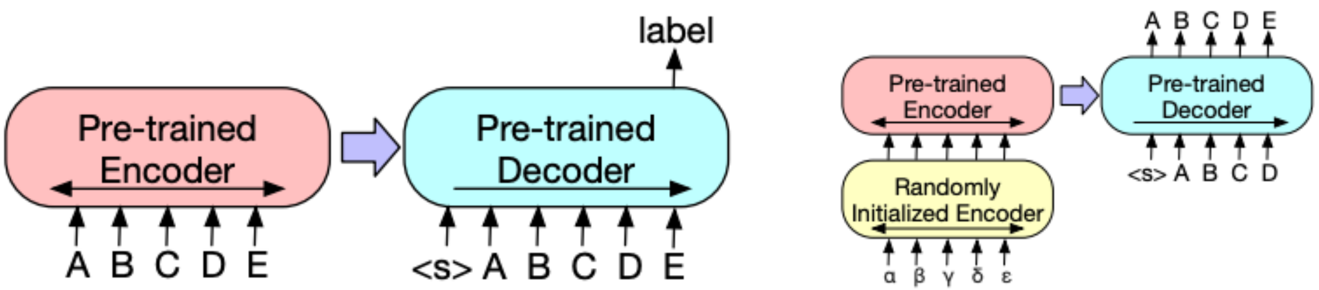


(c) BART: Inputs to the encoder need not be aligned with decoder outputs, allowing arbitary noise transformations. Here, a document has been corrupted by replacing spans of text with mask symbols. The corrupted document (left) is encoded with a bidirectional model, and then the likelihood of the original document (right) is calculated with an autoregressive decoder. For fine-tuning, an uncorrupted document is input to both the encoder and decoder, and we use representations from the final hidden state of the decoder.

Figure 1: A schematic comparison of BART with BERT (Devlin et al., 2019) and GPT (Radford et al., 2018).

BART Paper

BART



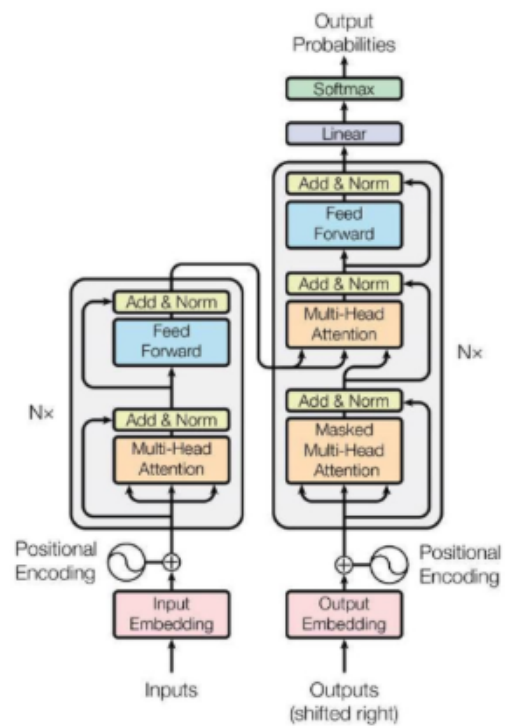
(a) To use BART for classification problems, the same input is fed into the encoder and decoder, and the representation from the final output is used.

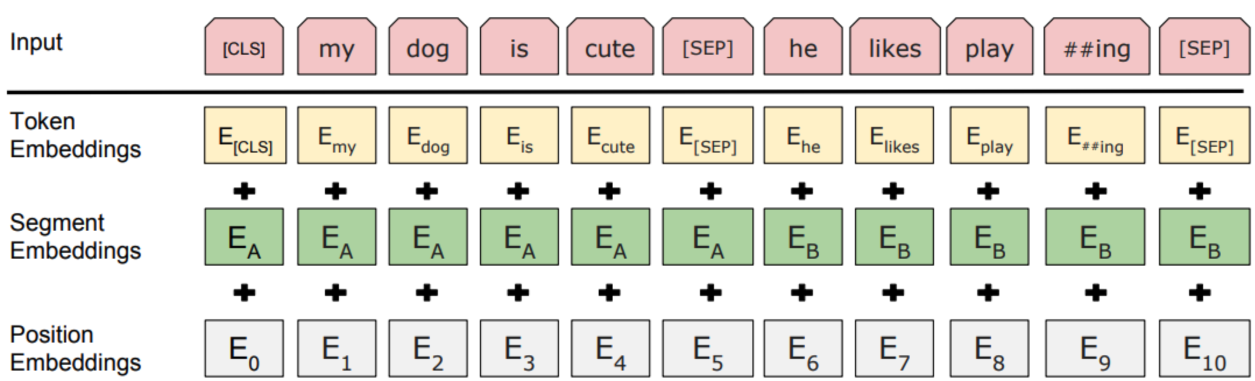
(b) For machine translation, we learn a small additional encoder that replaces the word embeddings in BART. The new encoder can use a disjoint vocabulary.

Figure 3: Fine tuning BART for classification and translation.

BART Paper

BERT Embeddings





Fine-Tuning Transformers for down-stream tasks

A methodology for fine-tuning transformers for classification tasks

1. **Pick Base pre-trained Architecture:** Pick a base pre-trained architecture as a starting point for your fine-tuning. Example: `bert-base-uncased` is one such pre-trained model that can be loaded through `Hugging Face Transformers Library`

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3. **Add fine-tuning layers:** Add fine-tuning layers on top of the pre-trained layers. Example, starting with the pooled embeddings, construct one or more dense layers (`Feed-Forward NN style`) to extract finer representations of the input. Add the output layer and its activation (typically softmax for classification tasks).

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4. **Set training schedule, hyper-parameters, etc:** Set up optimizer (e.g. ADAM), hyper-parameters, training schedule, etc for training.