



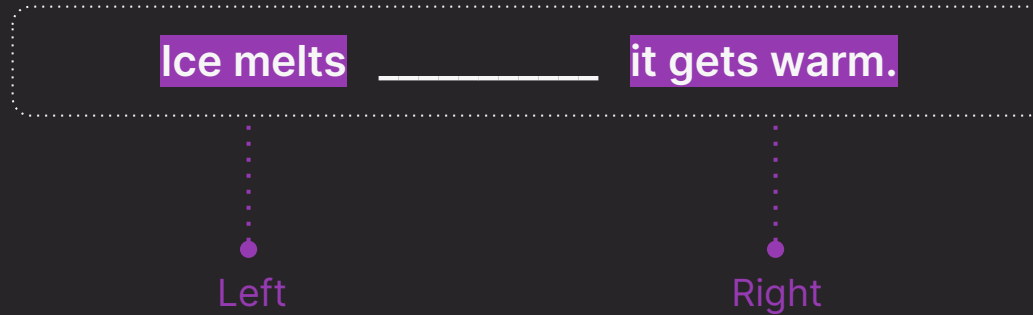
# Preparing for LLMs

**Video 2:** Pre trained transformers : BERT

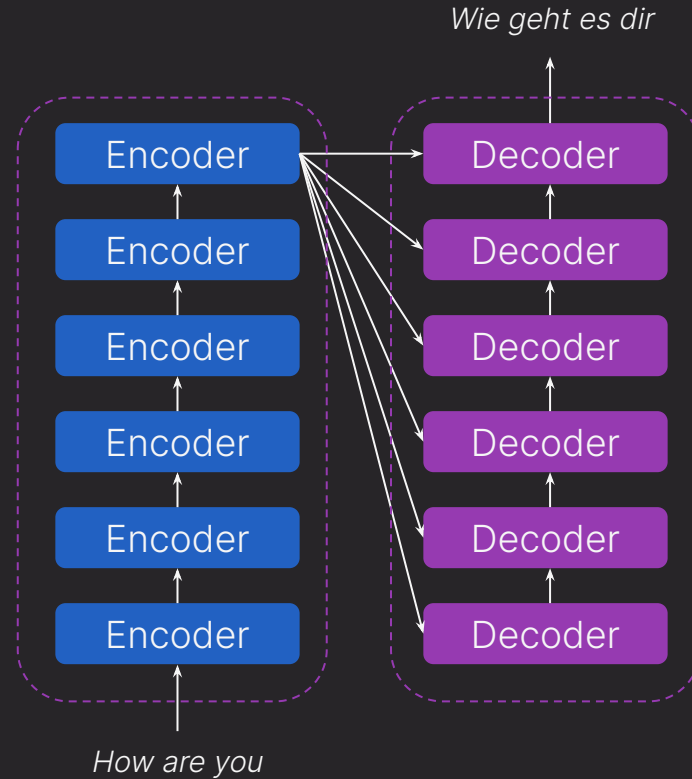
# 5. BERT

**B**idirectional **E**ncoder **R**epresentations from **T**ransformers

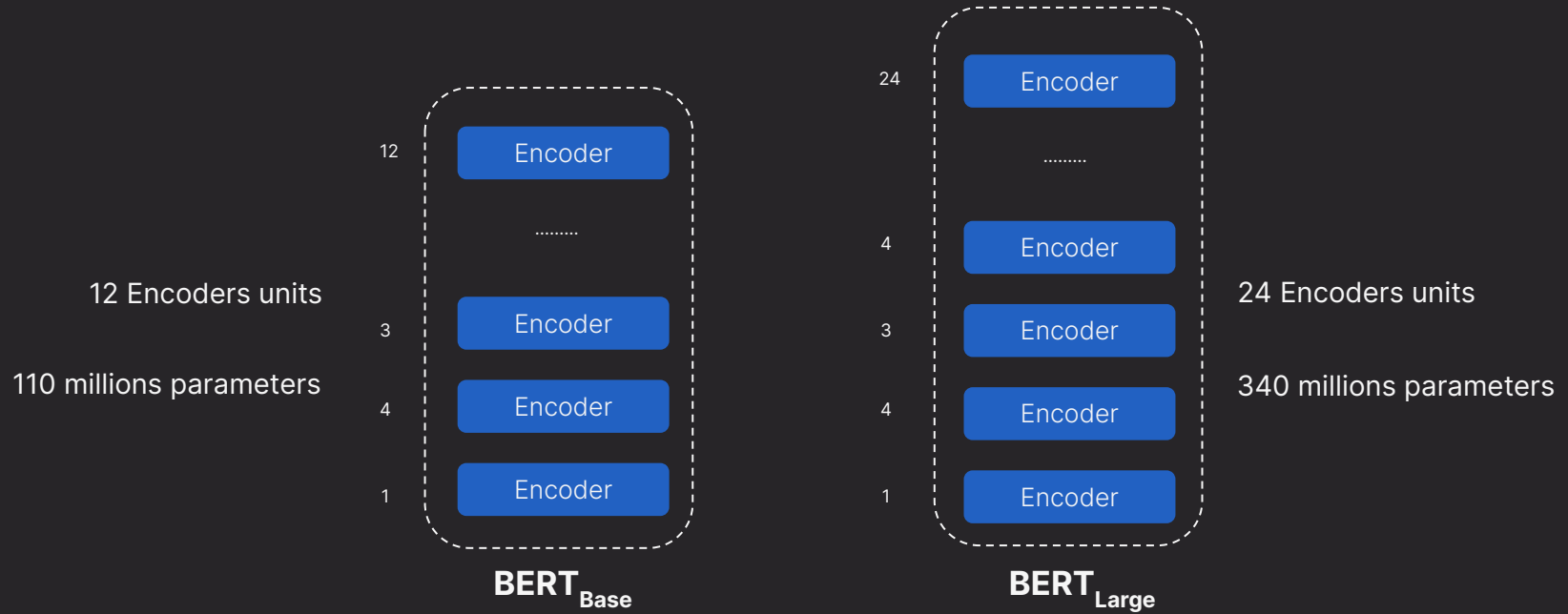
This method considers both left and right context of words in a sentence.



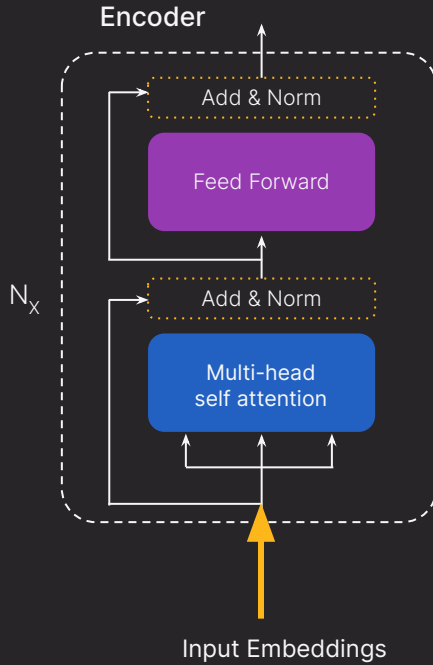
# Transformer



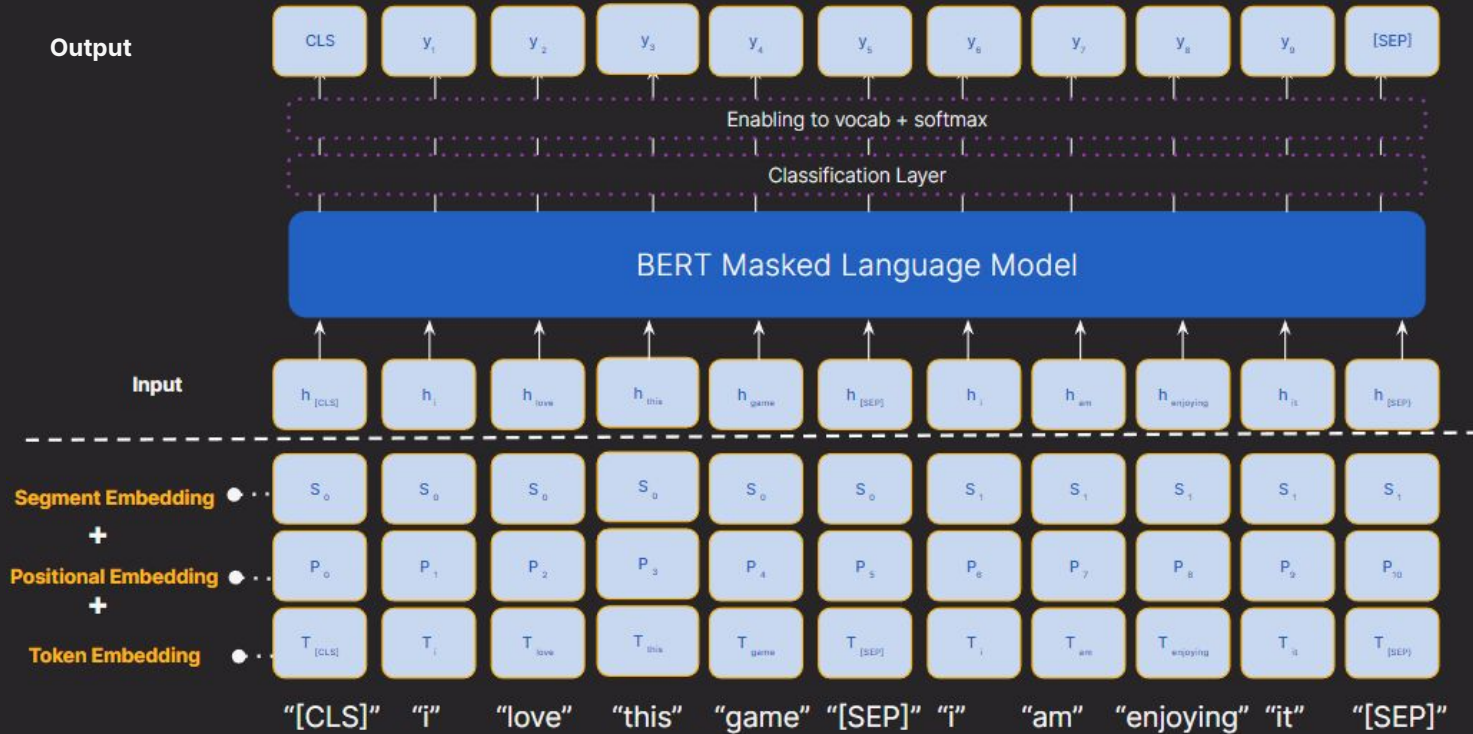
# Working of BERT

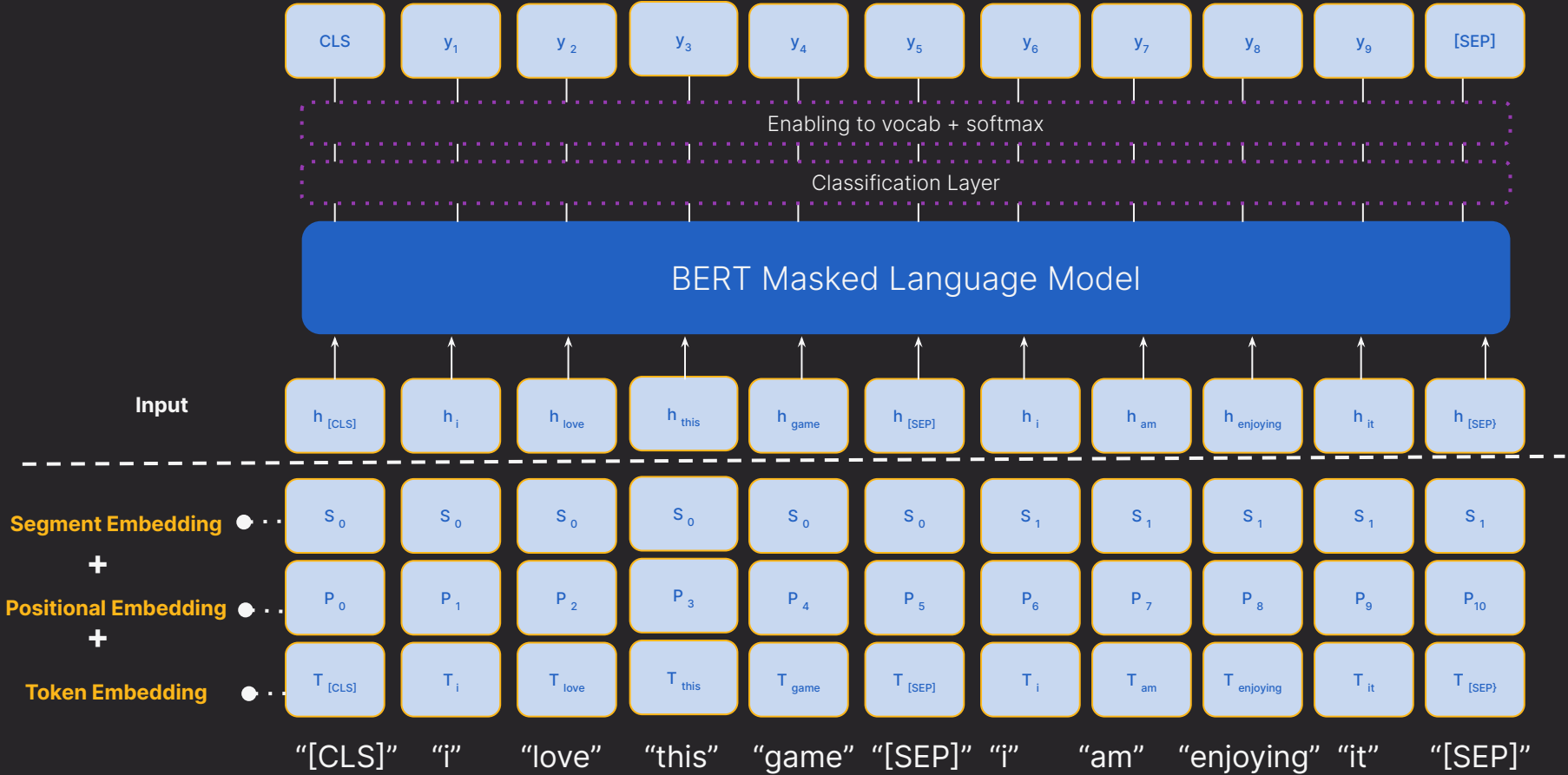


# Working of BERT

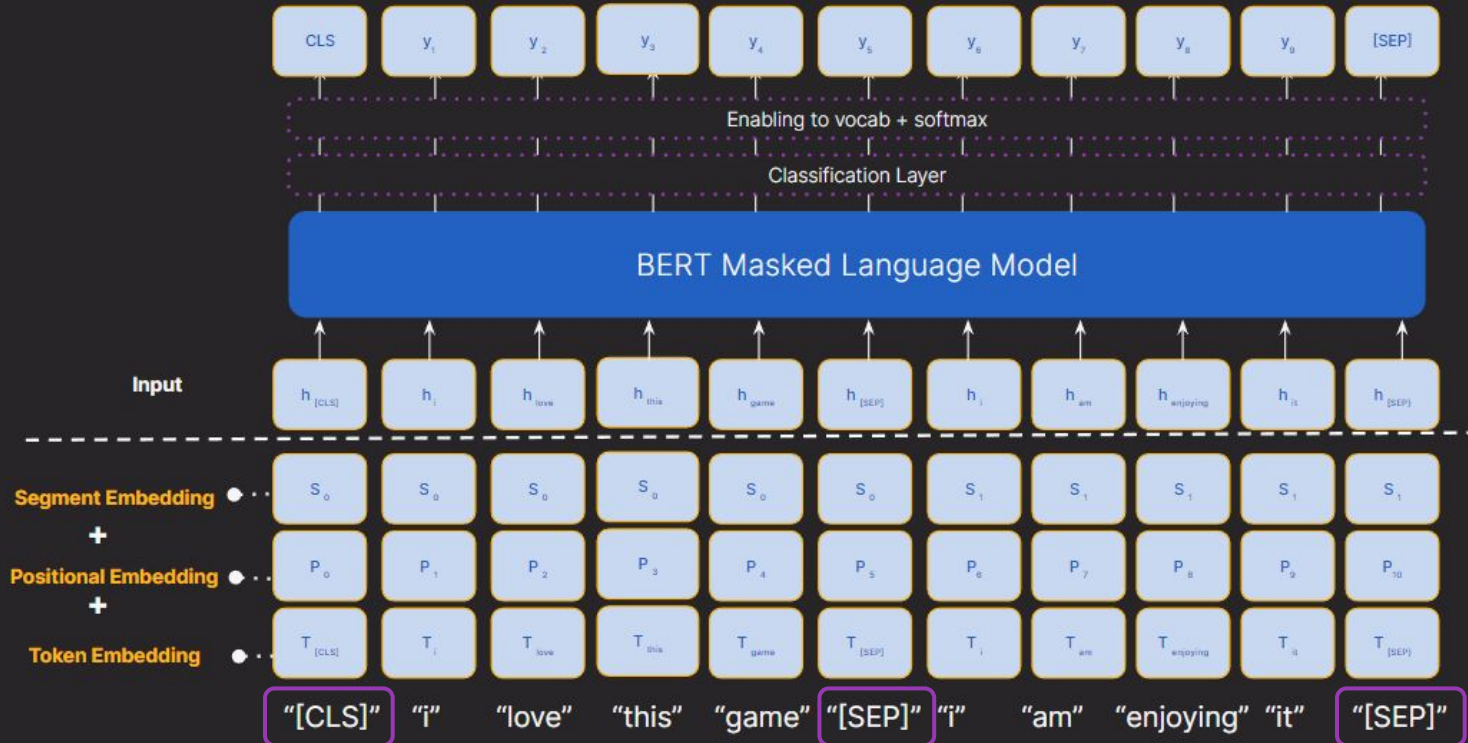


# Working of BERT





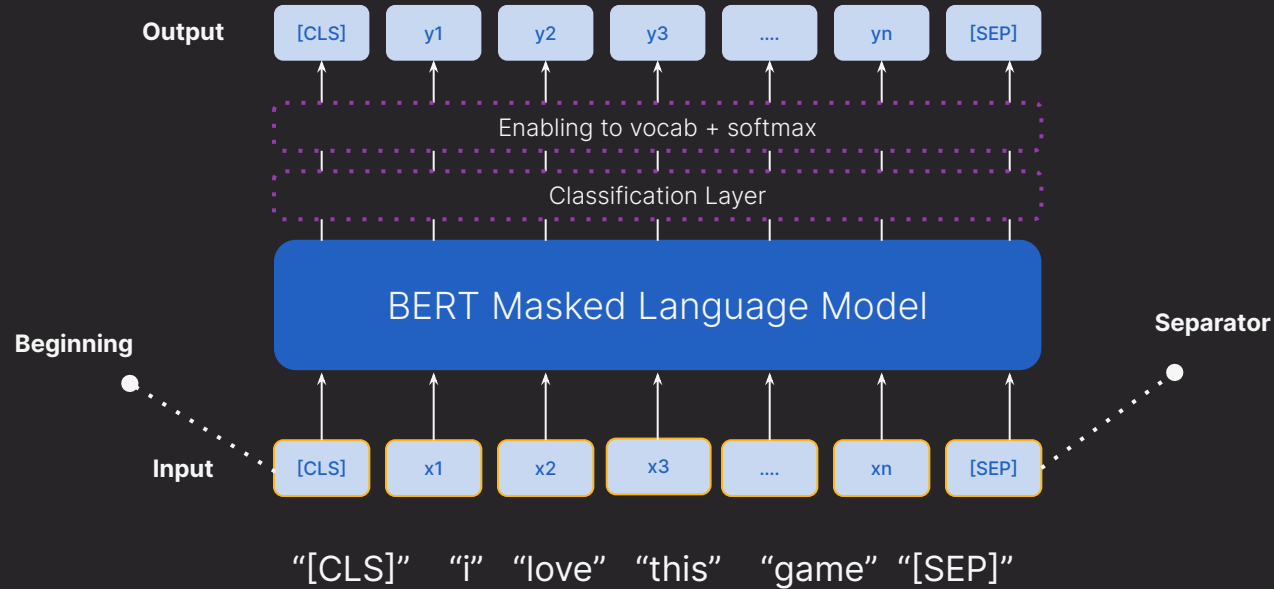
# Working of BERT

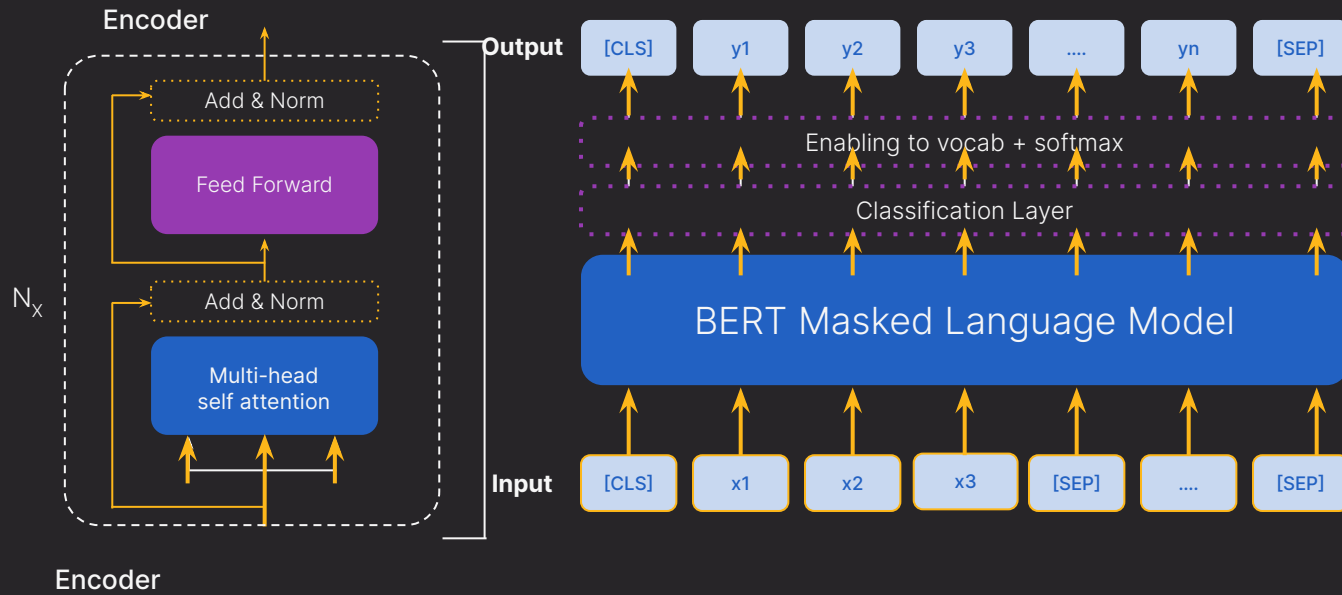


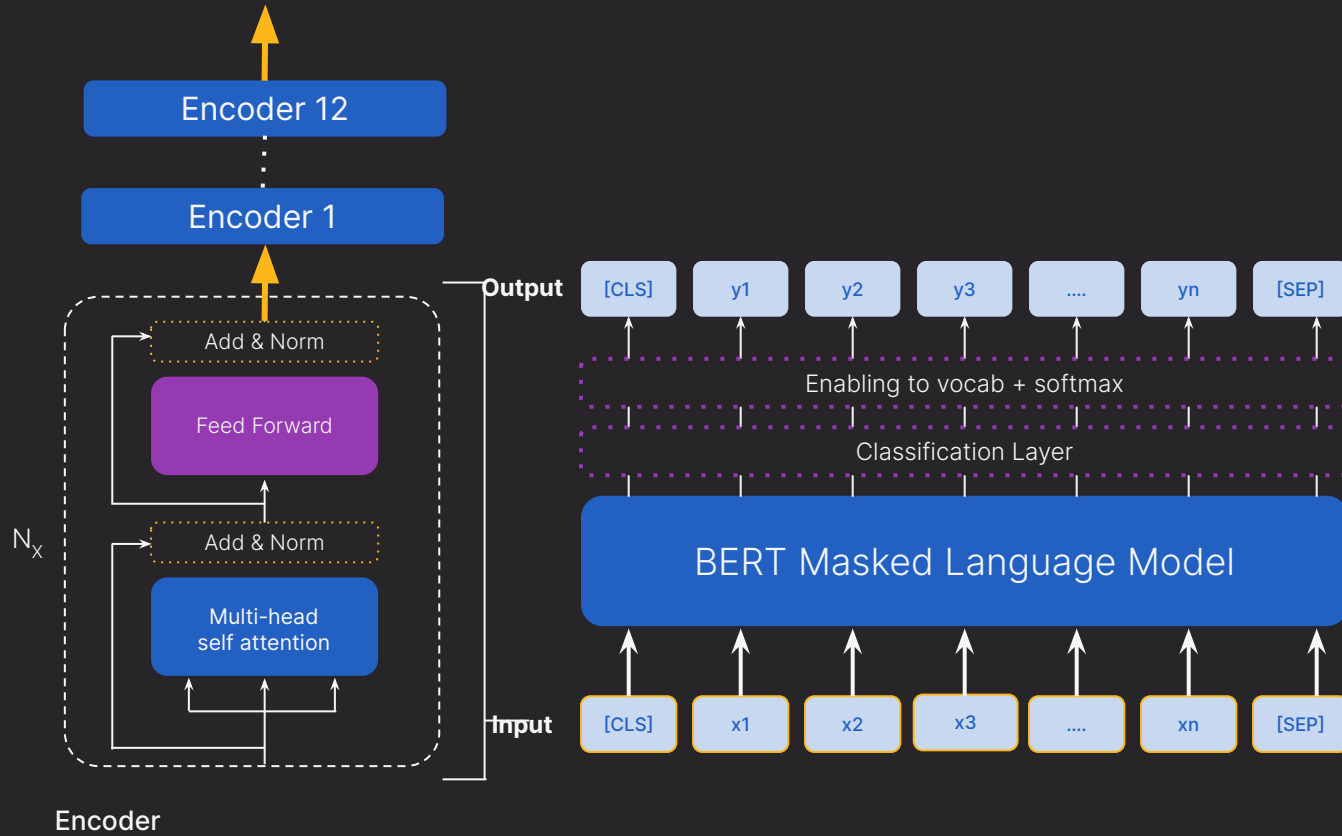


# Working of BERT

- Pre-training is done on a large amount of text to learn the contextual meaning.



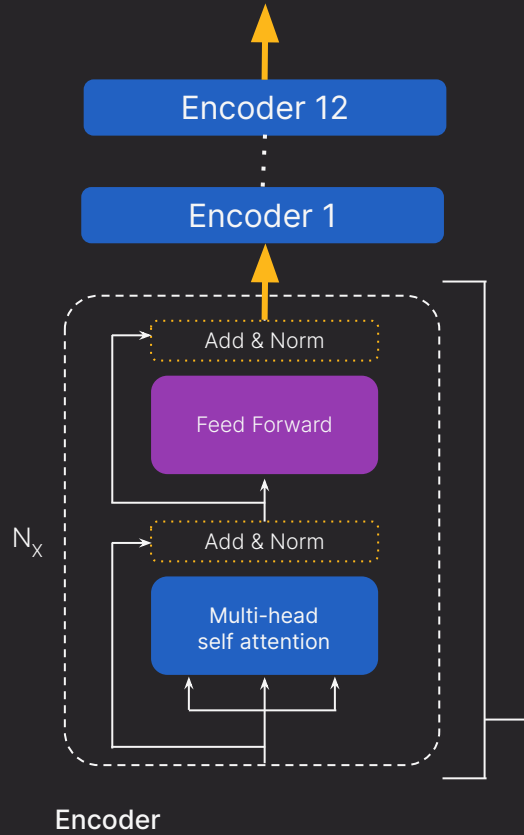




# BERT

1 Pre - Training

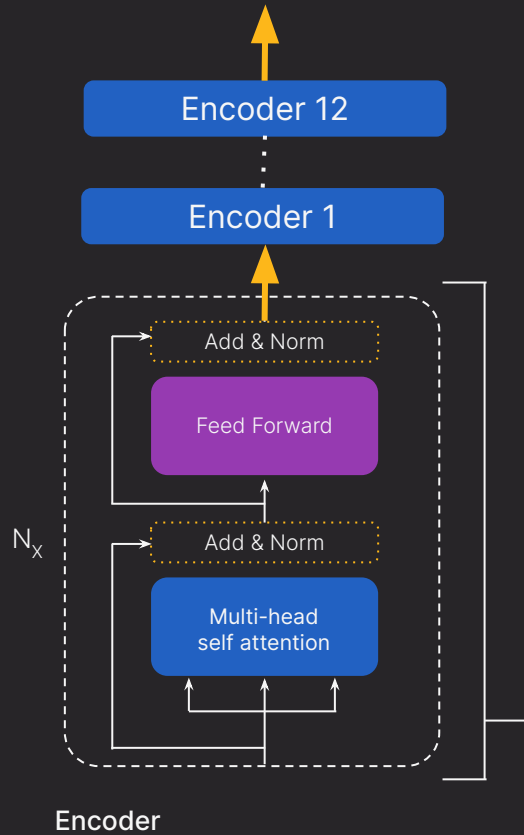
2 Fine-Tuning



# BERT

## 1 Pre - Training

- Wikipedia of **2500 million** words
- Book corpus data of **800 million** words



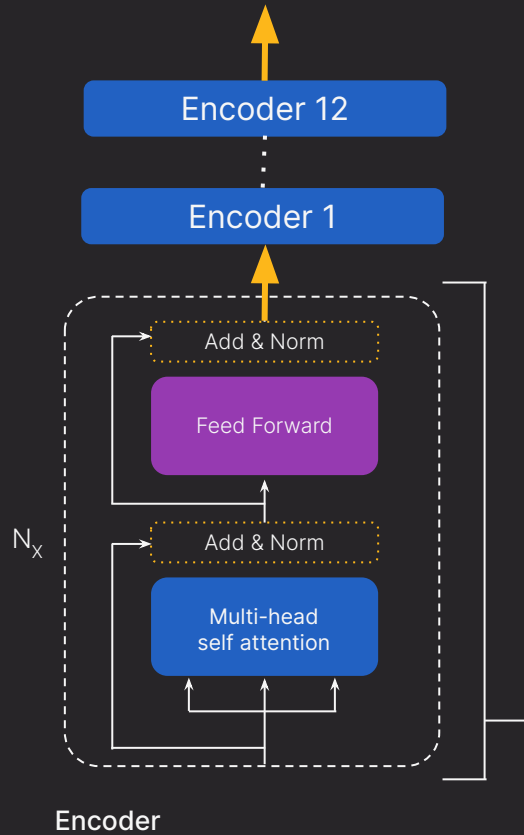
# BERT

## 1 Pre - Training

Challenge of defining prediction goal

Masked Language Model (MLM)

Next Sentence Prediction (NSP)



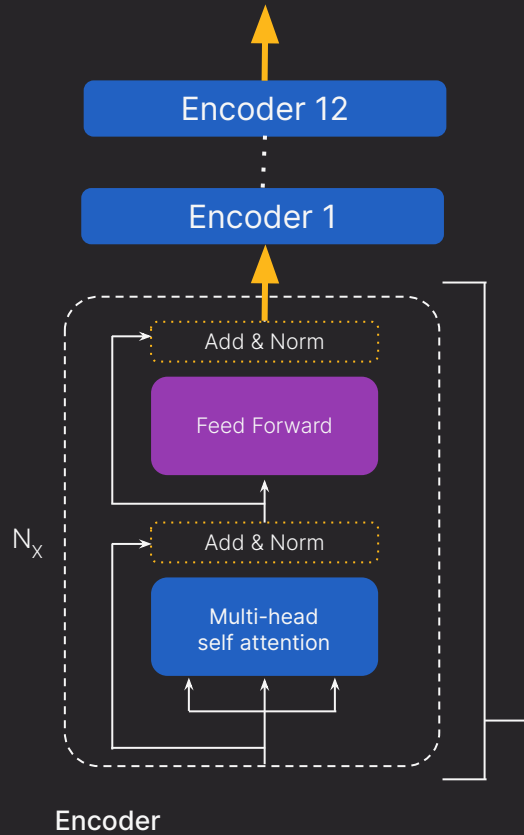
# BERT

## 1 Pre - Training

Challenge of defining prediction goal

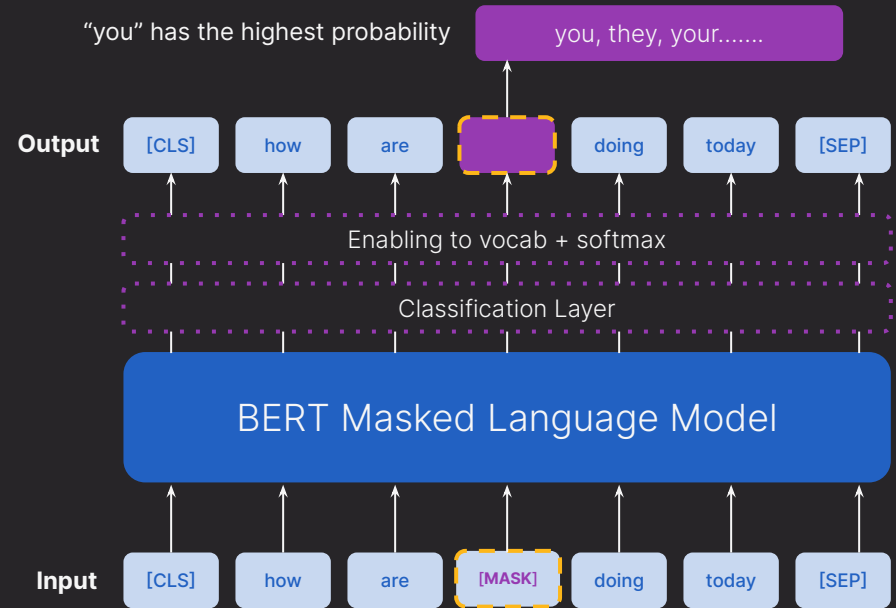
Masked Language Model (MLM)

Next Sentence Prediction (NSP)



# Masked Language Model (MLM)

- BERT **masks and replaces some words** in input sequences with symbols like [MASK], to be predicted by the model.





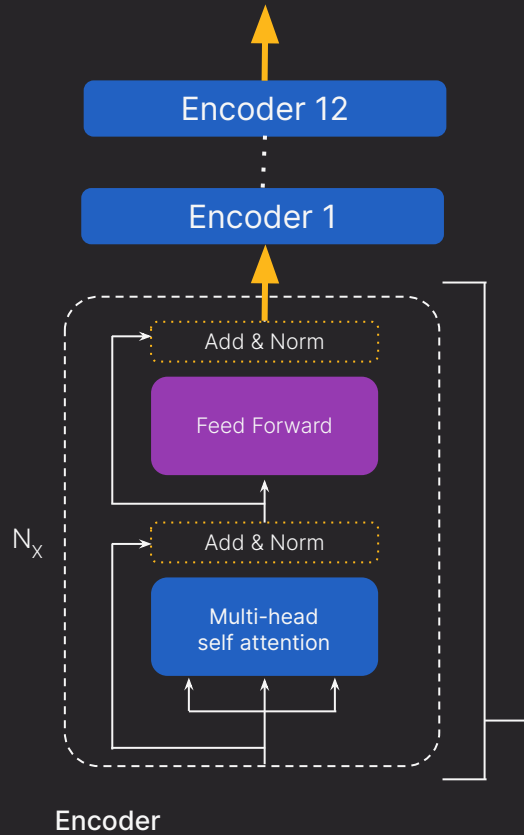
# BERT

## 1 Pre - Training

Challenge of defining prediction goal

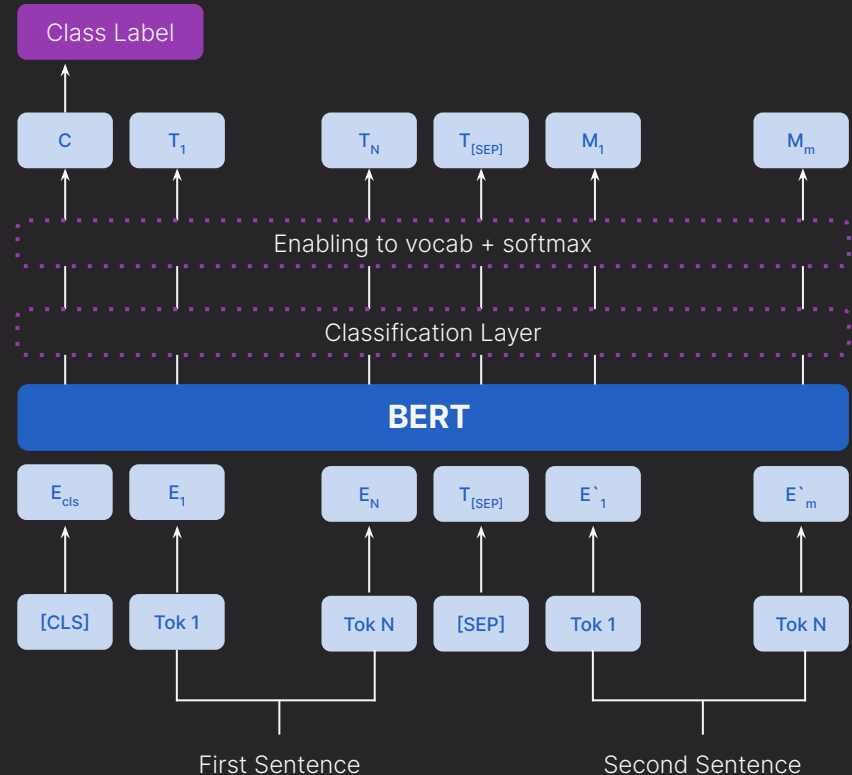
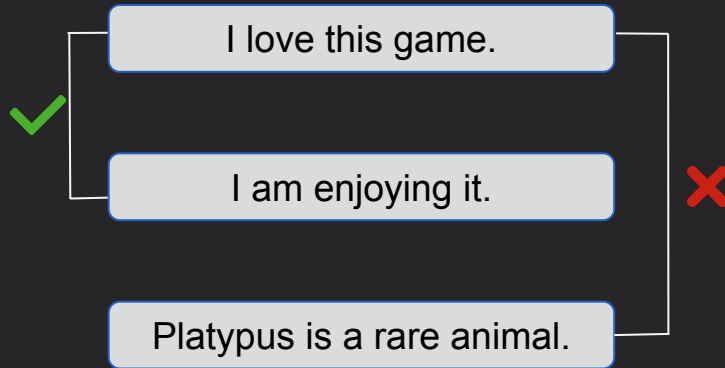
Masked Language Model (MLM)

Next Sentence Prediction (NSP)

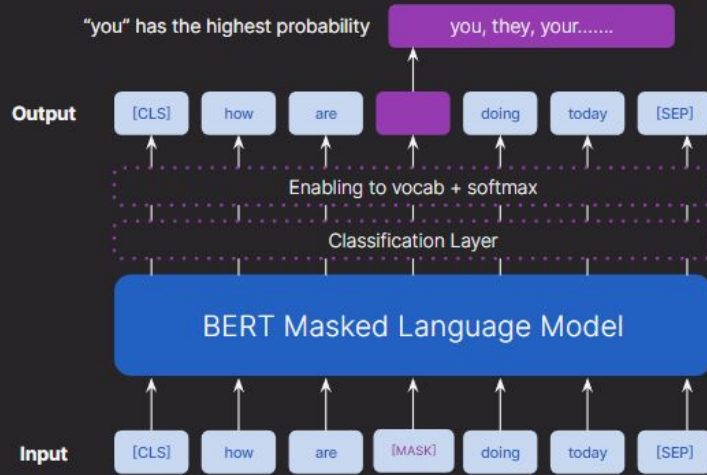


# Next Sentence Prediction (NSP)

- For a pair of sentences, BERT has to identify whether one sentence logically follows the next or not.

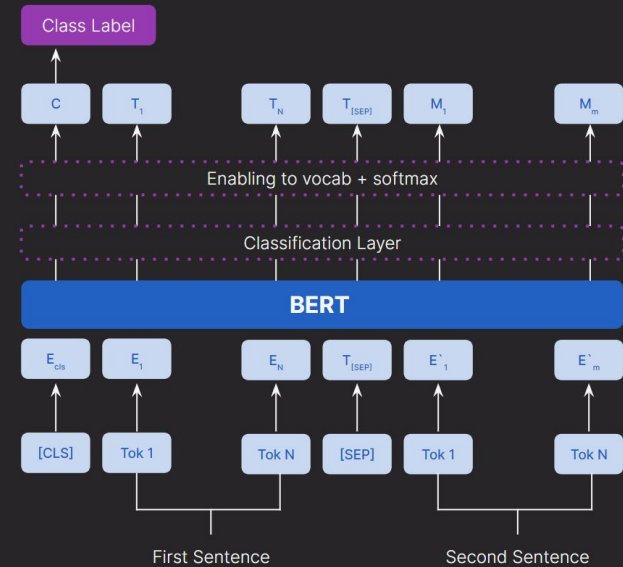


# Analysis



Masked Language Model (MLM)

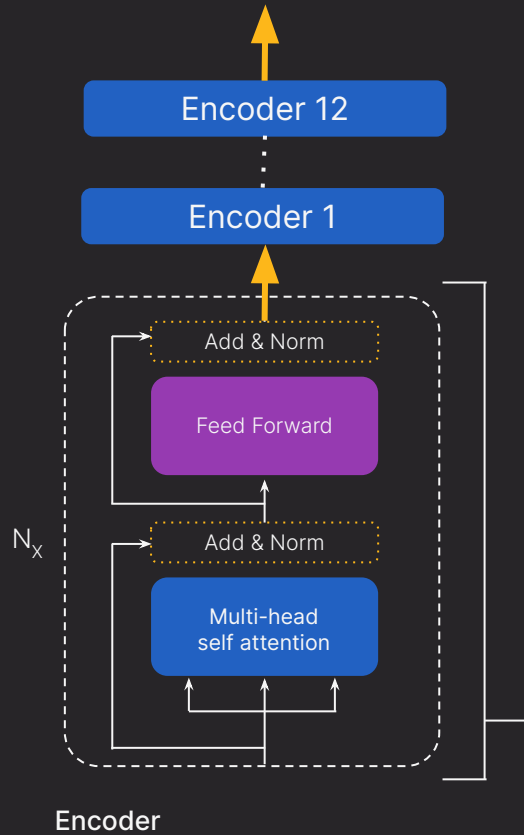
Understanding context within a sentence



Next Sentence Prediction (NSP)

Understand relationships between sentences

# BERT

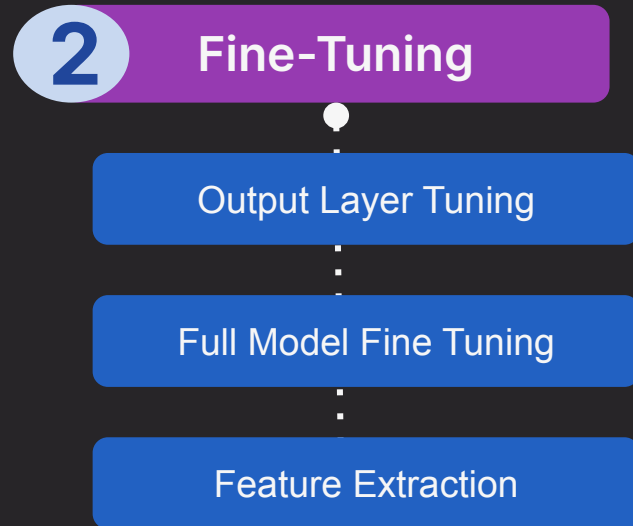


1 Pre - Training

2 Fine-Tuning

Task specific dataset

- ✓ Test Classification
- ✓ Sentiment Analysis
- ✓ NER
- ✓ POS tagging



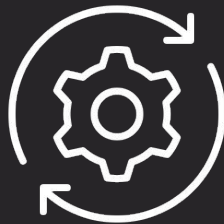
# Fine tuning

## Output Layer Tuning



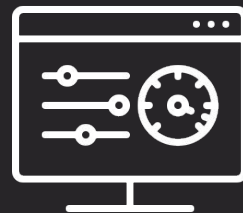
- Task specific outer layer is trained while freezing the lower layers

## Full Model Fine Tuning



- Fine tuning all the layers of the model.
- Effective for large dataset.

## Feature Extraction



1. Domain Adaptive helps the model in Feature Extraction
2. Fine tuning on specific tasks

# GLUE

**G**eneral **L**anguage **U**nderstanding **E**valuation

Measure performance of models on various language understanding challenges.



Rank	Name	Model	URL	Score	CoLA	SST-2	MRPC	STS-B	QQP
1	Microsoft Alexander v-team	Turing ULR v6		91.3	73.3	97.5	94.2/92.3	93.5/93.1	76.4/90.9
2	JDExplore d-team	Vega v1		91.3	73.8	97.9	94.5/92.6	93.5/93.1	76.7/91.1
3	Microsoft Alexander v-team	Turing NLR v5		91.2	72.6	97.6	93.8/91.7	93.7/93.3	76.4/91.1
4	DIRL Team	DeBERTa + CLEVER		91.1	74.7	97.6	93.3/91.1	93.4/93.1	76.5/91.0
5	ERNIE Team - Baldu	ERNIE		91.1	75.5	97.8	93.9/91.8	93.0/92.6	75.2/90.9
6	AliceMind & DIRL	StructBERT + CLEVER		91.0	75.3	97.7	93.9/91.9	93.5/93.1	75.6/90.8
7	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.8	71.5	97.5	94.0/92.0	92.9/92.6	76.2/90.8
8	HFL iFLYTEK	MacALBERT + DKM		90.7	74.8	97.0	94.5/92.6	92.8/92.6	74.7/90.6
9	PING-AN Omni-Sinitic	ALBERT + DAAF + NAS		90.6	73.5	97.2	94.0/92.0	93.0/92.4	76.1/91.0
10	T5 Team - Google	T5		90.3	71.6	97.5	92.8/90.4	93.1/92.8	75.1/90.6
11	Microsoft D365 AI & MSR AI & GATECH	MT-DNN-SMART		89.9	69.5	97.5	93.7/91.6	92.9/92.5	73.9/90.2
12	Huawei Noah's Ark Lab	NEZHA-Large		89.8	71.7	97.3	93.3/91.0	92.4/91.9	75.2/90.7
13	LG AI Research	ANNA		89.8	68.7	97.0	92.7/90.1	93.0/92.8	75.3/90.5

Click on a submission to see more information





# Preparing for LLMs

**Video 3:** Using Pre trained transformers : BERT