Lecture 13.

Contextual Word Embeddings

CS224n Natural Language Processing with Deep Learning

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Word Representation

Deep Learning is all about Representation Learning.

Building the right tools for learning representations is an important factor in achieving empirical success.

- Ashish Vaswani

Word Representation = 단어에 대한 표현

Word Embedding 을 통해 단어를 벡터로 표현함으로써 자연어를 실수 공간의 벡터로 변환

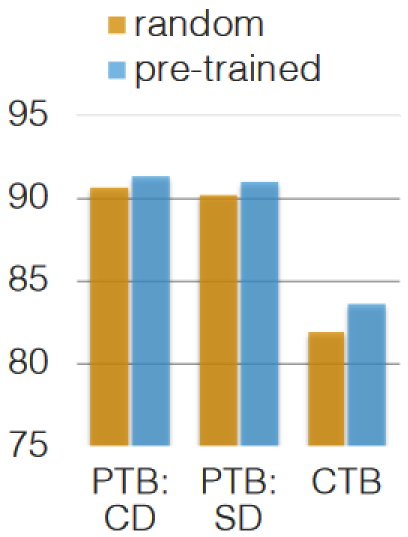
Pre-trained Word Vectors: The early years/Current Sense

	POS WSJ (acc.)	NER CoNLL (F1)
State-of-the-art*	97.24	89.31
Supervised NN	**96.37**	**81.47**
Unsupervised pre-training followed by supervised NN**	**97.20**	**88.87**
+ hand-crafted features***	97.29	89.59

-> rule based

-> Supervised Learning

-> Supervised Learning +
Unsupervised word representation
(Word2vec, Glove)



- Chen and Manning (2014)
  Dependency parsing
- Random: uniform(-0.01, 0.01)
- Pre-trained:
  - PTB (C & W): +0.7%
  - CTB (word2vec): +1.7%

Random Initialized < Pre-trained

(because we can train them for more words on much more data)

Tips for unknown words with word vectors

pre-trained word vector 사용 시 <UNK> 토큰 처리

<UNK> 1. dataset 에서 5회 이하로 등장하는 단어

2. train set 이 아닌, test set 에서만 등장하는 단어

Problem) No way to distinguish different <UNK> words

Solution)

1. char-level models to build vectors
2. if <UNK> word at test time appears in unsupervised word embeddings, use that vector
3. assign <UNK> word a random vector, adding them to vocabulary

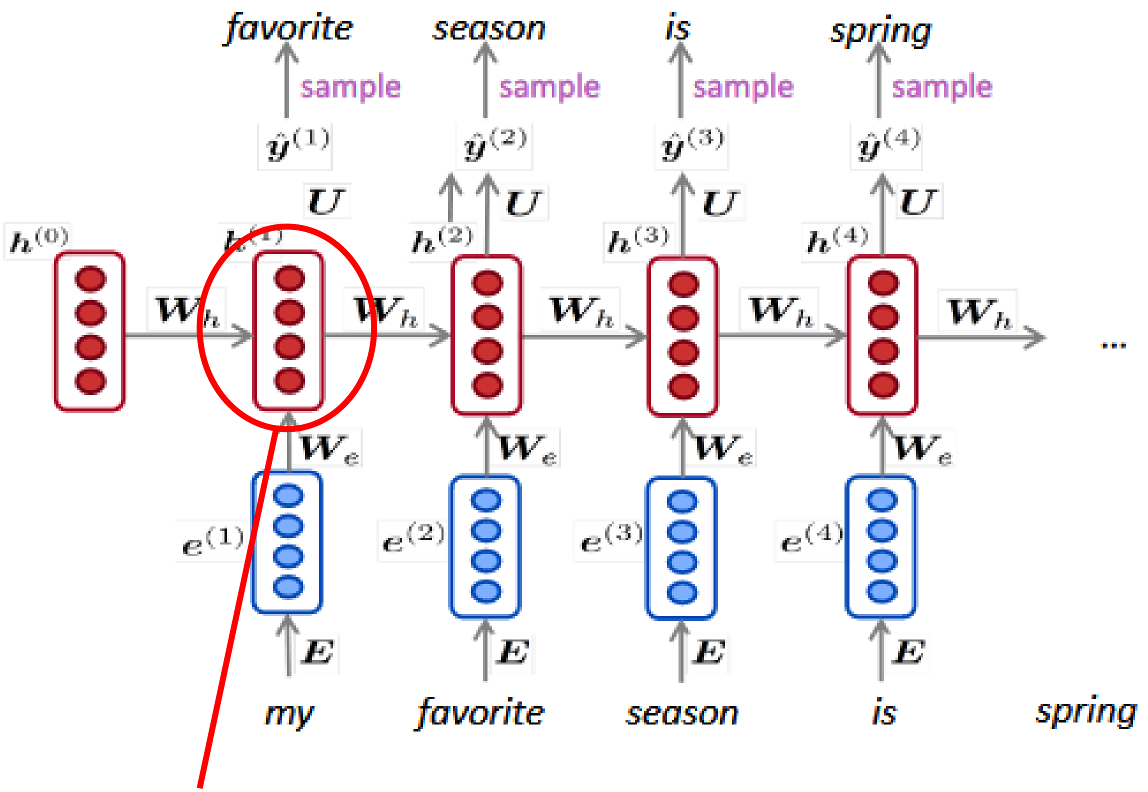
Representation for a word

one representation of words with word vectors (Word2Vec, GloVe, fastText)

Problems)

1. Always the same representation for a word type regardless of the context in which a word token occurs
2. Have one representation for a word, but words have different aspects, including semantic, syntactic behavior, and register/connotations

Representation for a word



NLM (Neural Language Modeling)

LSTM 층은 다음 단어를 예측하도록 학습

각 LSTM 층에서 context-specific word representation 을 계산하므로 문맥 유지

actual representation of a word in context → already invented a way to have context-based

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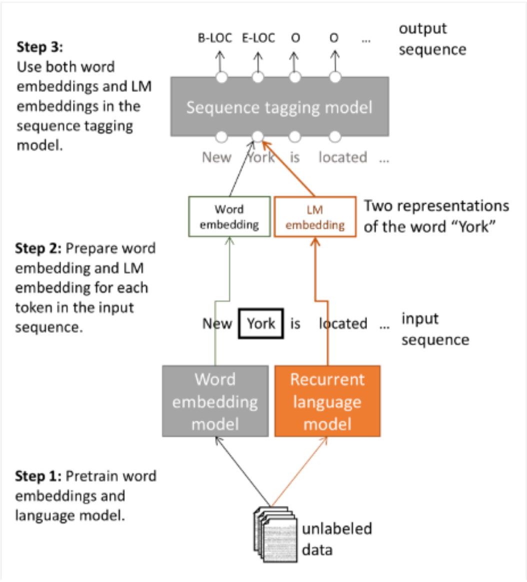
Pre-ELMo

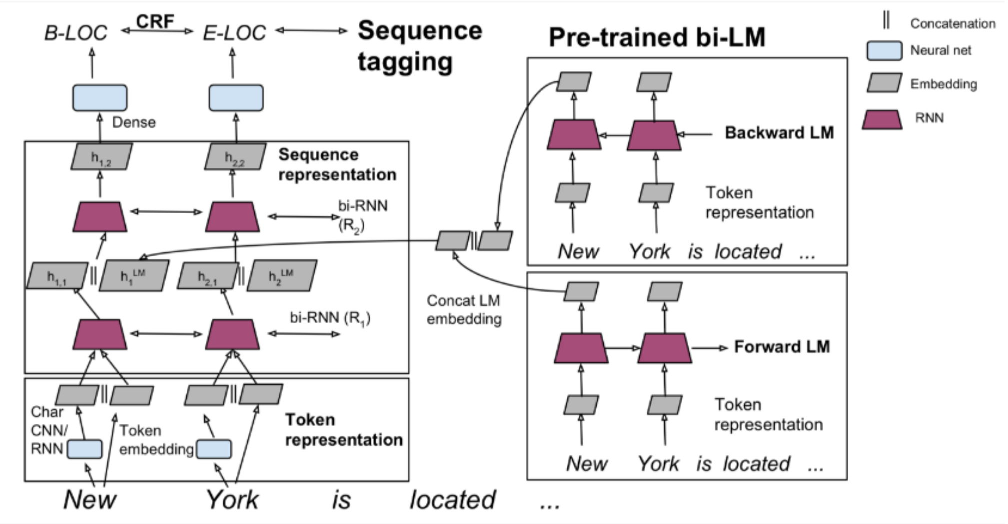
TagLM – "Pre-ELMo"

semi-supervised approach where we train NLM on large unlabeled corpus,

rather than just word vectors

=> semi-supervised learning with pre-trained word vector





$$\mathbf{h}_{k,1} = [\overrightarrow{\mathbf{h}}_{k,1}; \overleftarrow{\mathbf{h}}_{k,1}; \mathbf{h}_k^{LM}].$$

Pre-ELMo

[STEP 1]

- Word Embedding model 로 word vector 학습 (Word2Vec, GloVe)
- NLM model 로 word vector 학습 (bi-LSTM)

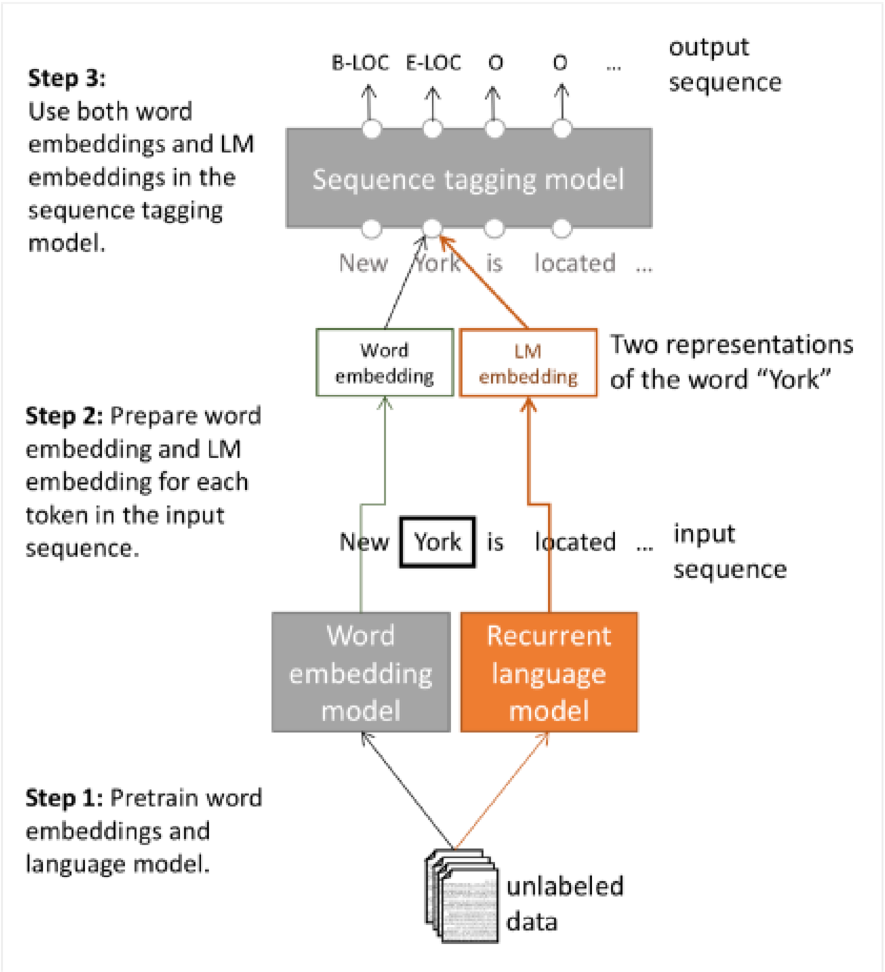
[STEP 2]

- Word Embedding 과 LM Embedding 을 input sequence 로 구성

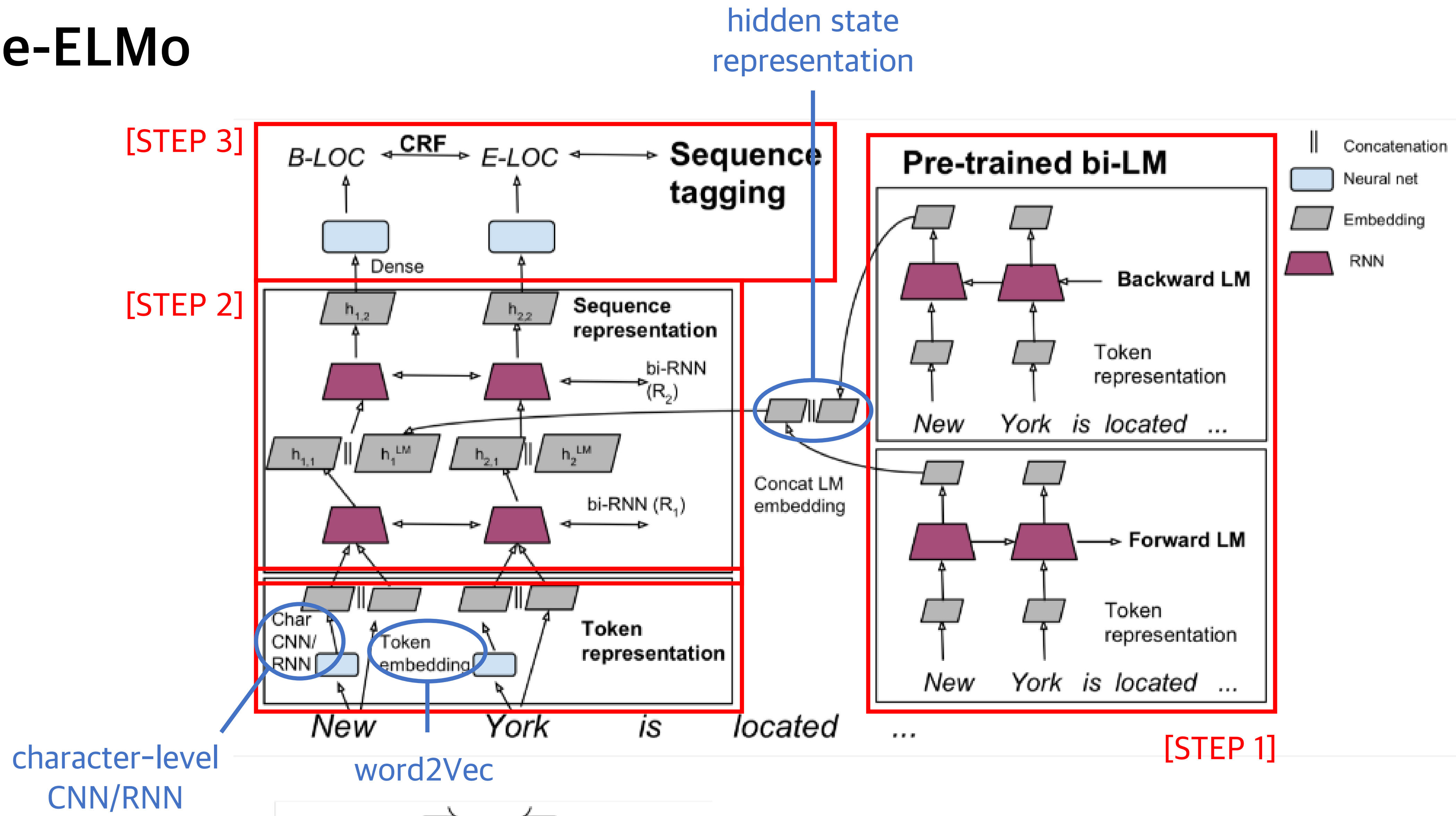
[STEP 3]

- sequence tagging model 에 Word Embedding 과 LM Embedding 을 input 으로 입력

-> feature word vector 와 context word vector 모두 사용



Pre-ELMo



$$\mathbf{h}_{k,1} = [\overrightarrow{\mathbf{h}}_{k,1}; \overleftarrow{\mathbf{h}}_{k,1}; \mathbf{h}_k^{LM}].$$

ELMo

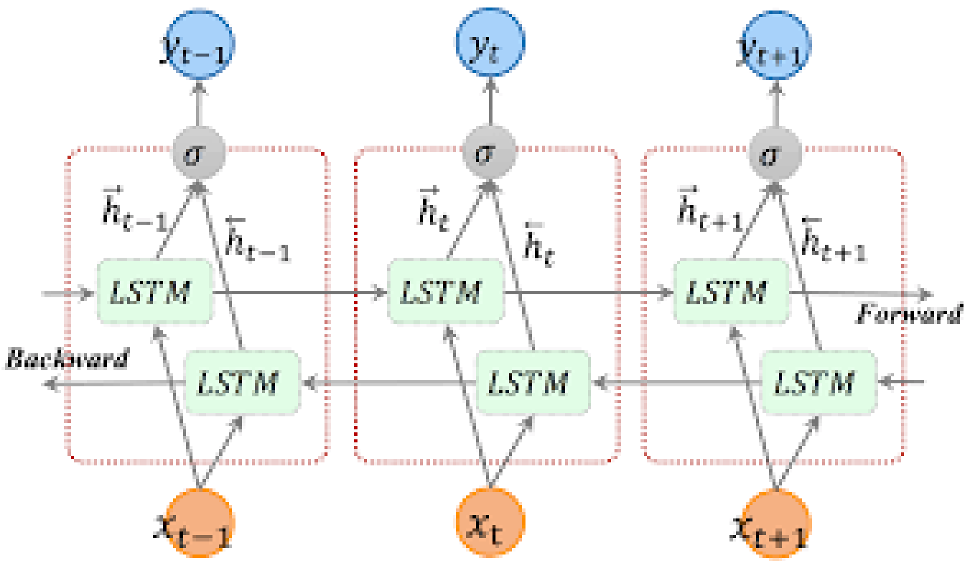
ELMO: Embeddings from Language Models

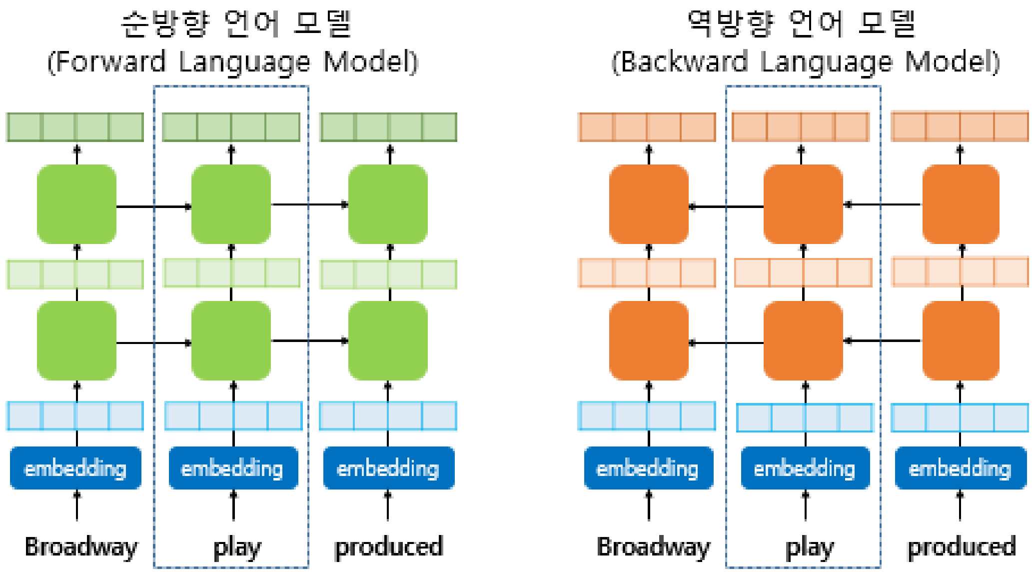
Deep contextualized word representations

- Breakout version of word token vectors/contextual word vectors
- Learn word token vectors using long contexts not context windows

- Use 2 bi-LSTM layers
    - Lower layer is better for lower-level syntax e.g. Part-of-speech tagging, NER
    - Higher layer is better for higher-level sematics e.g. Sentiment, Question Answering
- Use character CNN to build initial word representation only
  (= dispense with having word representation together)
- Use 4096 dim hidden/cell LSTM state with 512 dim projections to next input

ELMo





- 양방향 RNN

  순방향 RNN 의 은닉 상태와 역방향 RNN의

  은닉상태를 다음 층의 입력으로 보내기 전에

  concatenate

- biLM(Bidirectional Lanauage Model)

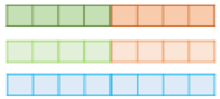
  순방향 언어 모델과 역방향 언어 모델이

  <u>각각의 은닉 상태만을</u> 다음 은닉층으로 전달하여

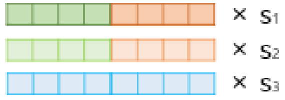
  훈련 시킨 후에 은닉 상태를 concatenate

ELMo

1) 각 층의 출력값을 연결(concatenate)한다.

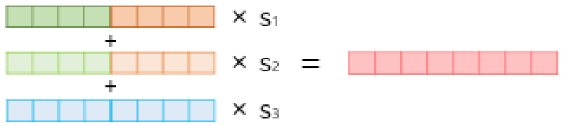


2) 각 층의 출력값 별로 가중치를 준다.



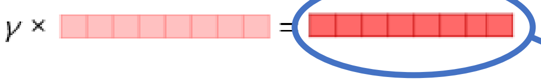
이 가중치를 여기서는 s_1, s_2, s_3라고 합시다.

3) 각 층의 출력값을 모두 더한다.

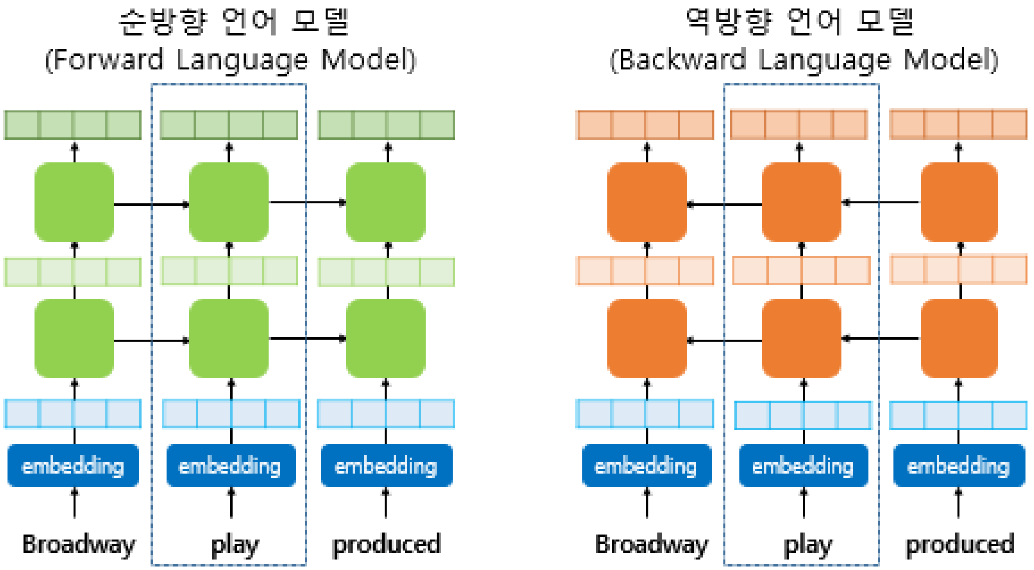


2)번과 3)번의 단계를 요약하여 가중합(Weighted Sum)을 한다고 할 수 있습니다.

4) 벡터의 크기를 결정하는 스칼라 매개변수를 곱한다.



이 스칼라 매개변수를 여기서는 γ이라고 합시다.



$$
\begin{aligned}
R_k &= \{\mathbf{x}_k^{LM}, \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} \mid j = 1, \ldots, L\} \\
&= \{\mathbf{h}_{k,j}^{LM} \mid j = 0, \ldots, L\},
\end{aligned}
$$

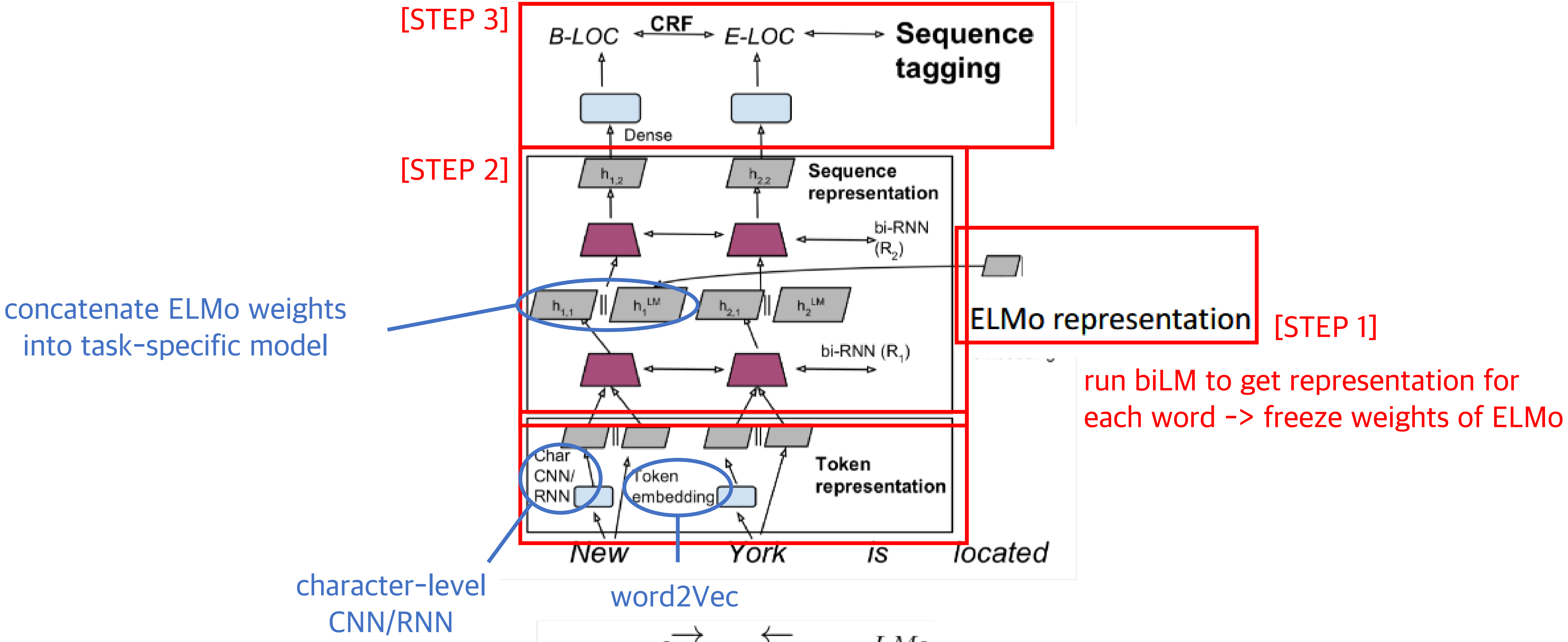
hidden state of kth layer

-> use all layers of NLM

$$
\mathbf{ELMo}_k^{task} = E(R_k; \Theta^{task}) = \gamma^{task} \sum_{j=0}^{L} s_j^{task} \mathbf{h}_{k,j}^{LM}
$$

ELMo representation

ELMo



$$\mathbf{h}_{k,1} = [\overrightarrow{\mathbf{h}}_{k,1}; \overleftarrow{\mathbf{h}}_{k,1}; \mathbf{h}_k^{LM}].$$

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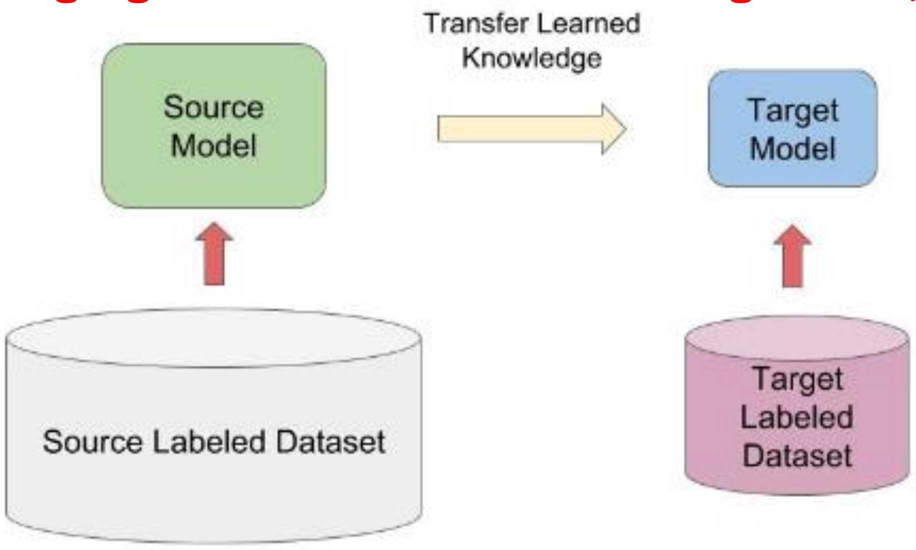
ULMFit

ULMFit : Universal Language Model Fine-tuning for Text Classification

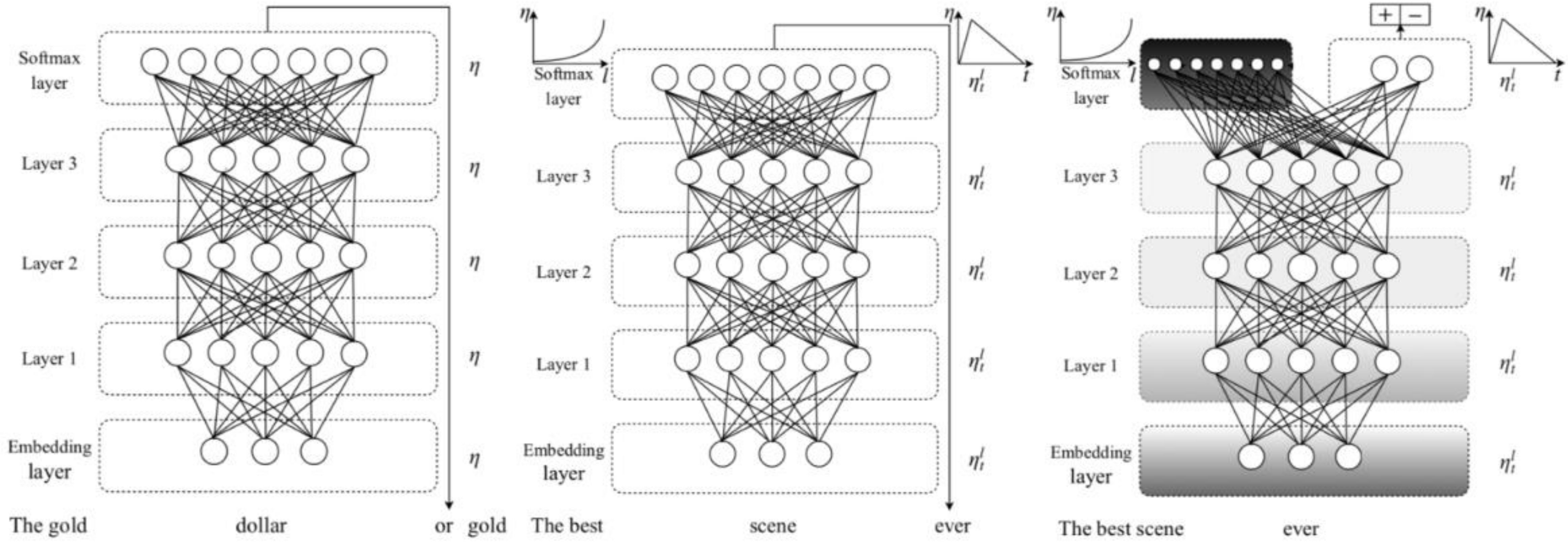
general idea of transferring NLM knowledge, applied to text classification

big language model

target task (e.g. NER)



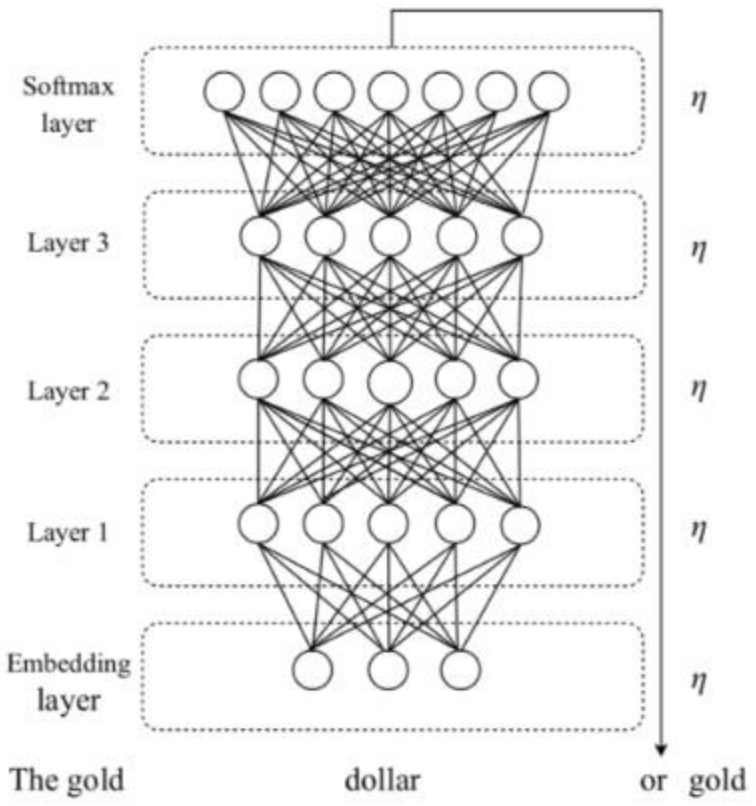
ULMFit



(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

일반 언어 모델 학습 과제 맞춤형 언어 모델 튜닝 과제 분류기 튜닝

ULMFit

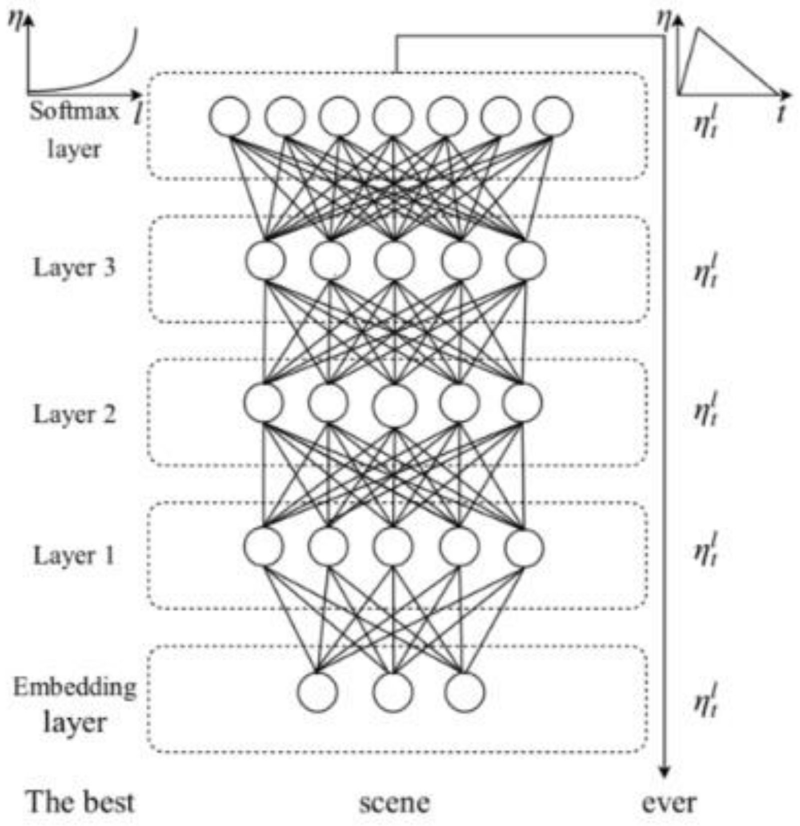


(a) LM pre-training

일반 언어 모델 학습

- 3-layer bi-LSTM Language Model 로 pre-trained
- 논문에서는 Wikipedia 의 정제된 28,595 개의 article 과 1억 개의 word 를 pre-training

ULMFit



(b) LM fine-tuning

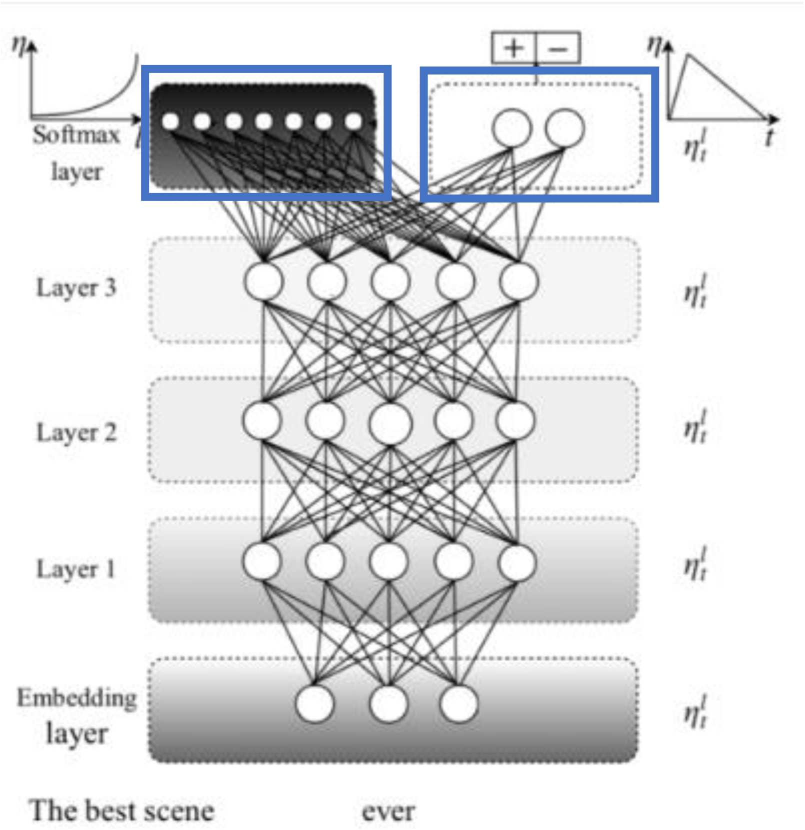
과제 맞춤형 언어 모델 튜닝

- 일반 언어 모델을 주어진 task에 맞게 조정하여 추가 학습
  학습 시 다른 네트워크가 아닌 동일한 네트워크를 사용하며, 네트워크에 대해 다른 objective 를 적용

- 주어진 task 에 100개의 텍스트와 대응되는 100개의 label 이 있는 경우, 100개의 텍스트를 사용하여 언어 모델을 튜닝

- 튜닝 시 사용하는 2가지 방법
  - Discriminative Fine-tuning
  - Slanted triangular learning rates

ULMFit



(c) Classifier fine-tuning

과제 분류기 튜닝

- 상위 계층의 softmax 층을 얼리고,
  다른 prediction unit 을 연결하여 특정 과제에 대한 예측 수행

Contents

Transformer models

All of these models are Transformer architecture models … so maybe we had better learn about Transformers?

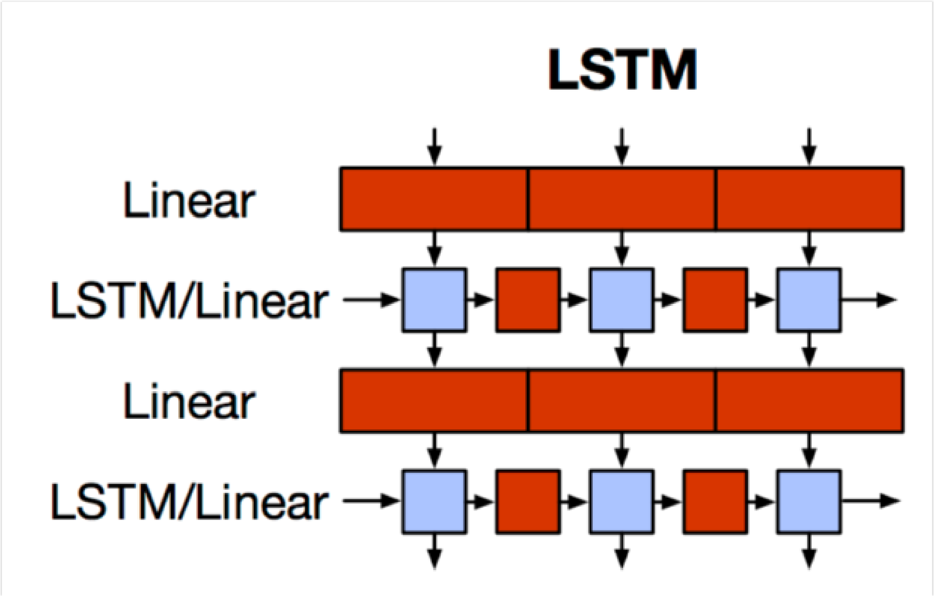
ULMfit	GPT	BERT	GPT-2
Jan 2018	June 2018	Oct 2018	Feb 2019
Training:	Training	Training	Training
1 GPU day	240 GPU days	256 TPU days ~320–560 GPU days	~2048 TPU v3 days according to a reddit thread
fast.ai	OpenAI	Google AI	OpenAI

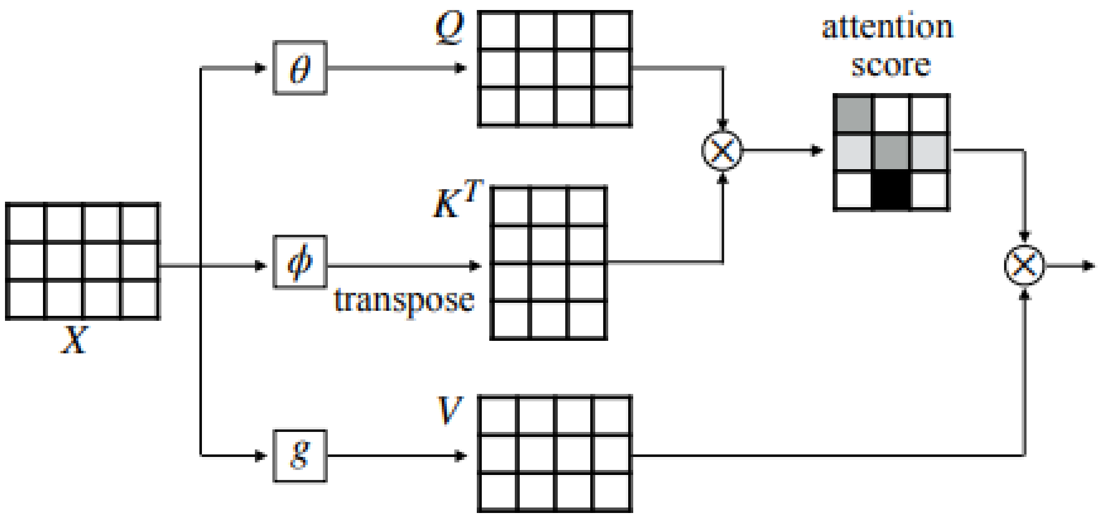
Transformer

RNNs are inherently sequential but we want parallelization

Despite GRUs and LSTMs, RNNs still need attention mechanism to deal ling range dependencies

-> What if attention gives us access to any state?

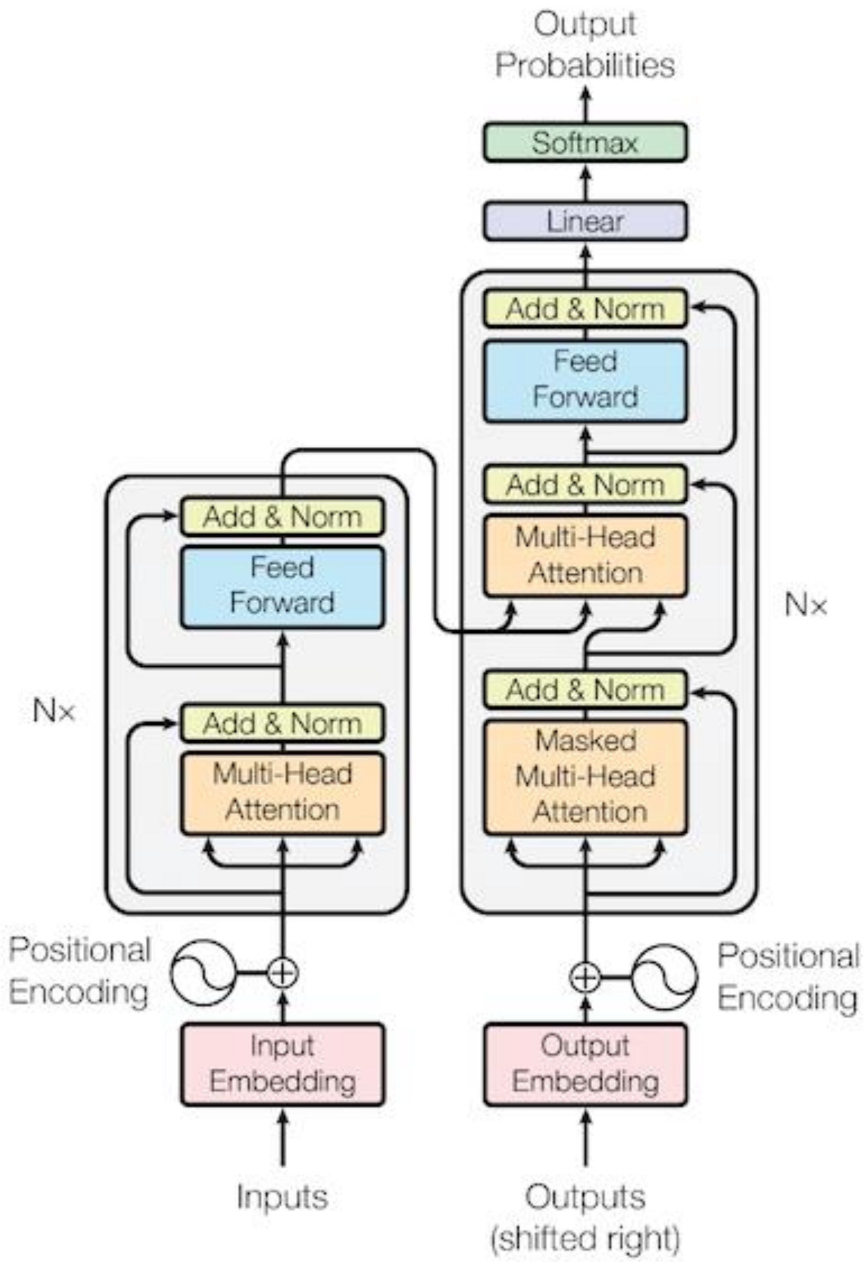




Transformer

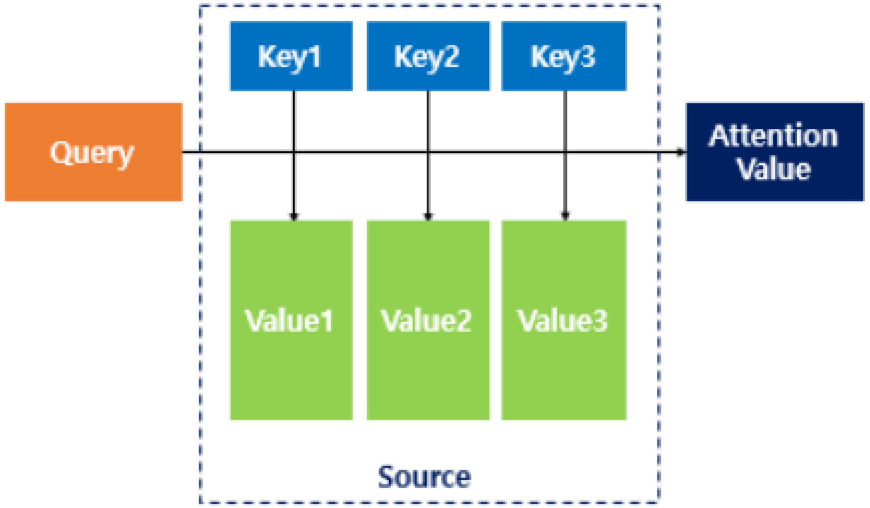
Transformer Overview

- Non-recurrent sequence-to-sequence encoder-decoder model
- Predict each translated word
- Final cost/error function is standard cross-entropy error on top of a softmax classifier
- Task : machine translation with parallel corpus



Transformer

Self-attention

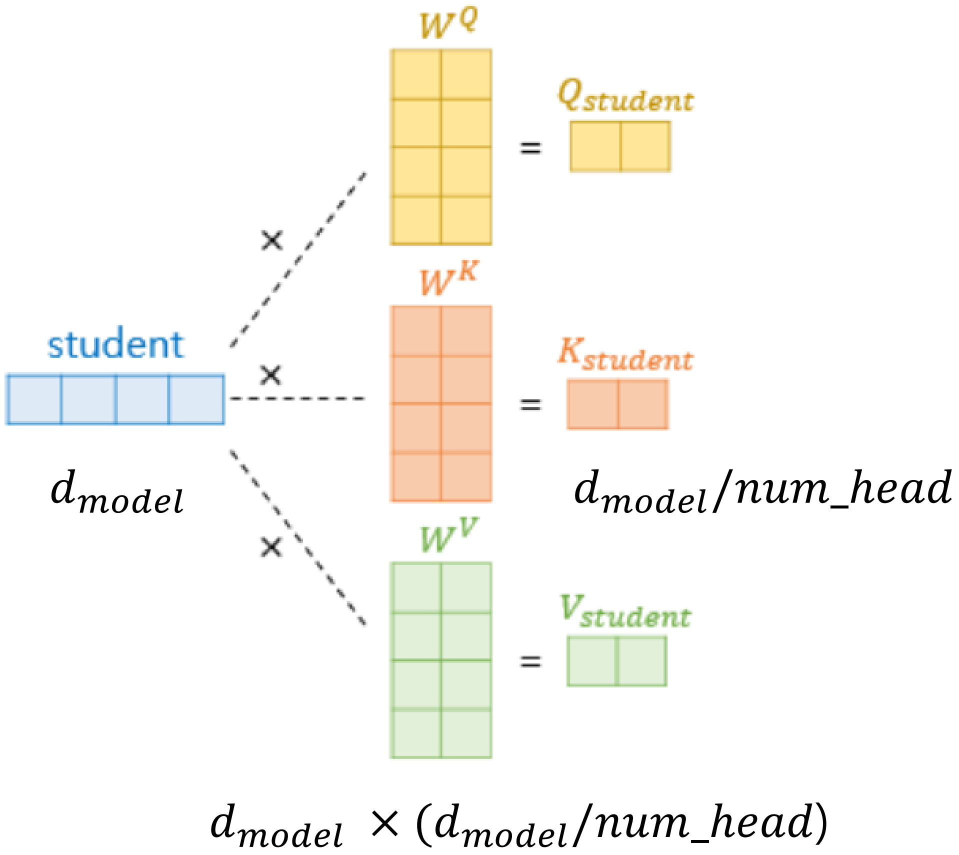


Query : 입력 문장의 모든 단어 벡터들

Key : 입력 문장의 모든 단어 벡터들

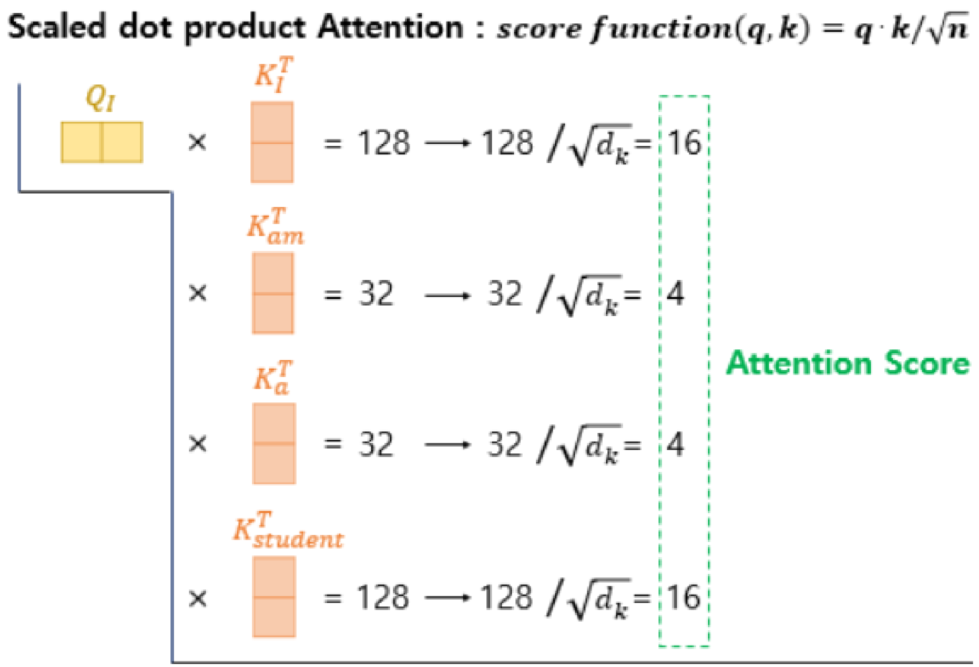
Value : 입력 문장의 모든 단어 벡터들

Dot-Product Attention

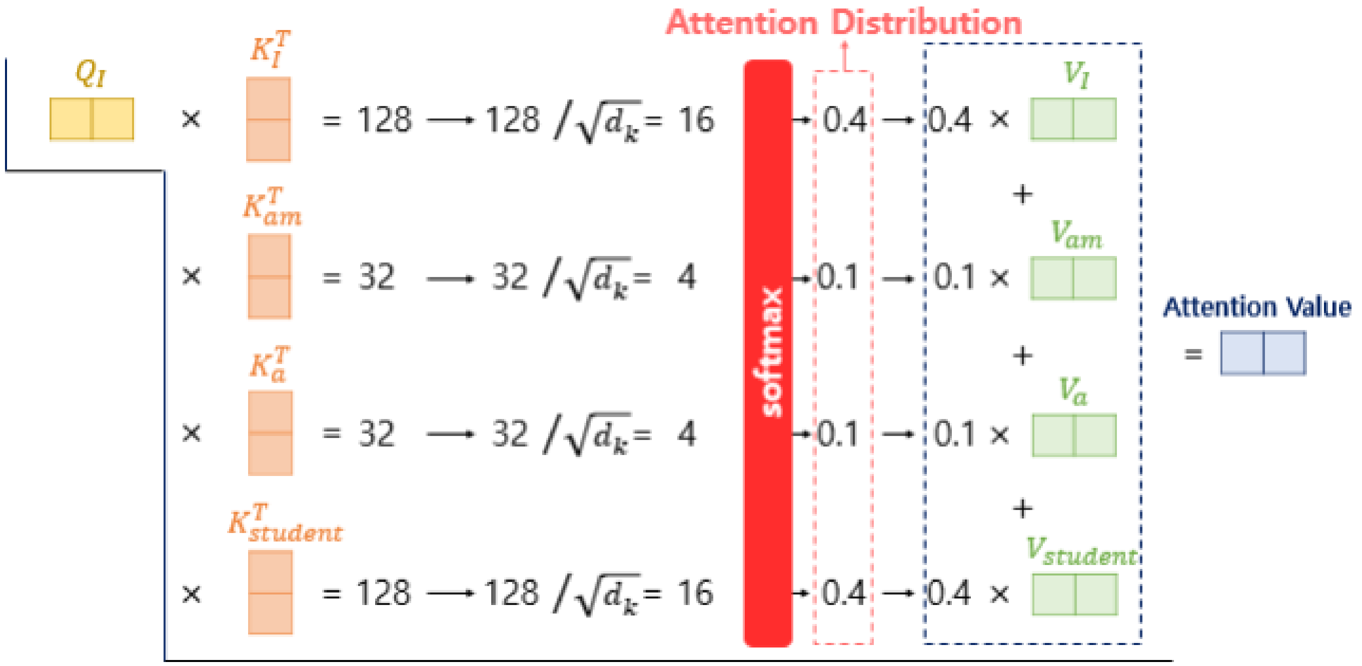


Transformer

Dot-Product Attention



attention score 계산

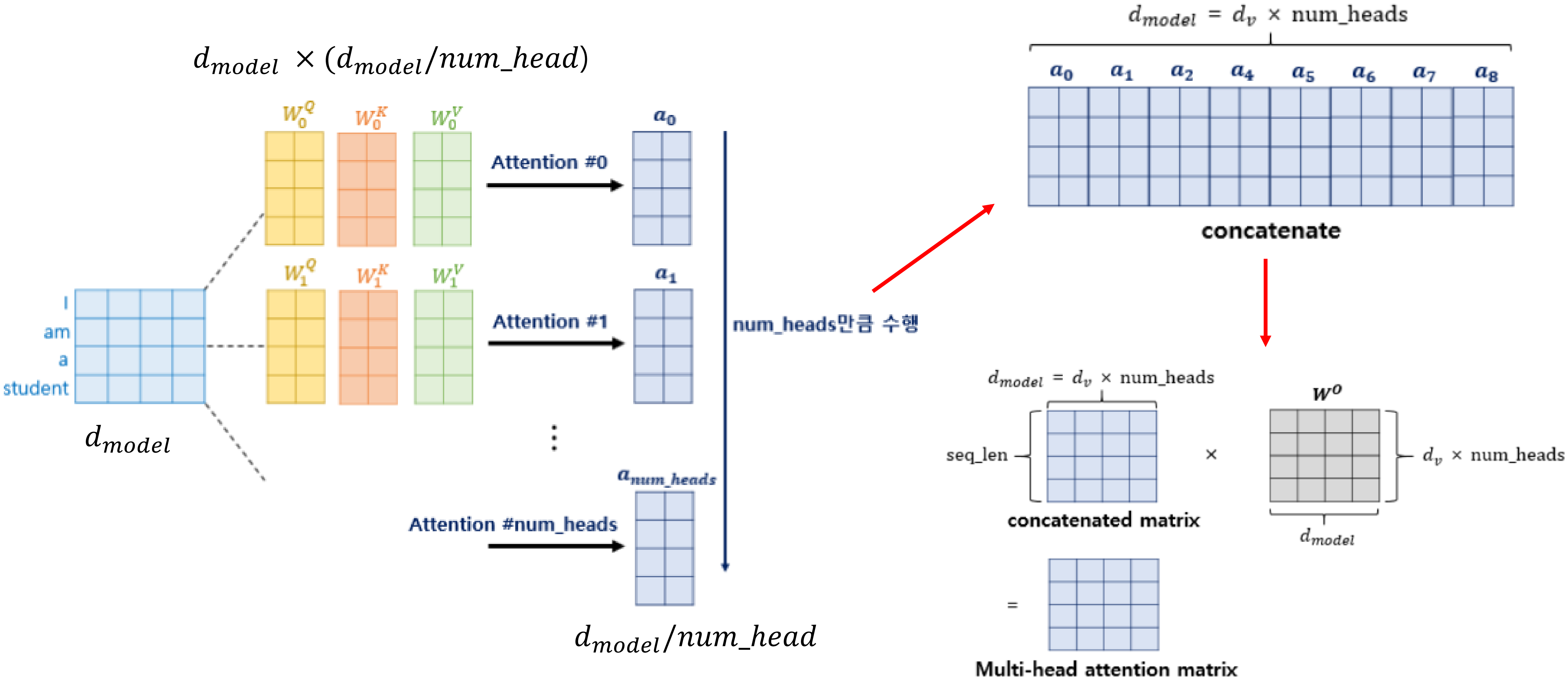


attention distribution/value 계산

$$=> \quad A(q, K, V) = \sum_i \frac{e^{q \cdot k_i}}{\sum_j e^{q \cdot k_j}} v_i$$

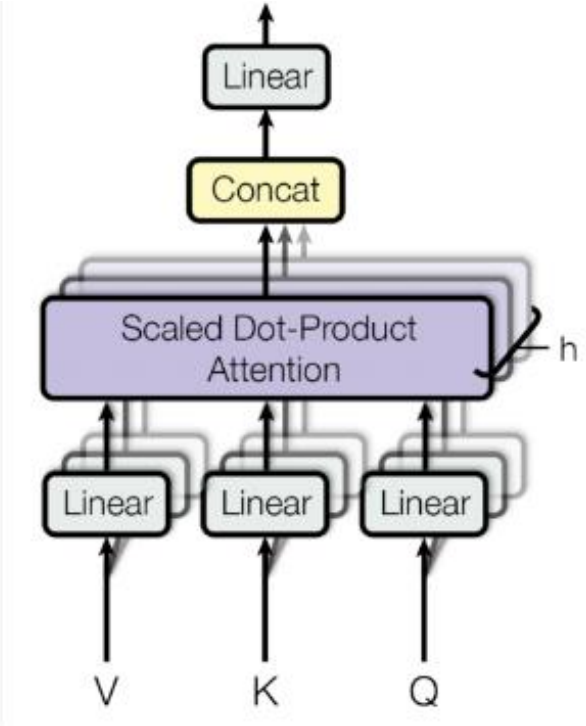
Transformer

Multi-head attention



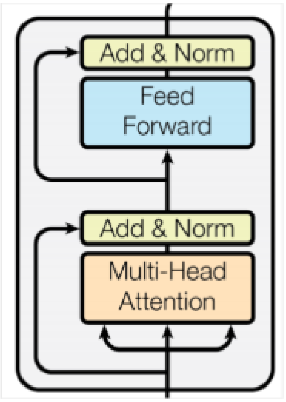
Transformer

Multi-head attention



$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head}_1, ..., \mathrm{head}_h)W^O$$
$$\text{where } \mathrm{head}_i = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Transformer Block



- Each block has two "sublayers"

1. Multihead attention
2. 2-layer feed-forward NNet (with ReLU)

Each of these two steps also has:

Residual (short-circuit) connection and LayerNorm

LayerNorm(x + Sublayer(x))

Layernorm changes input to have mean 0 and variance 1,
per layer and per training point (and adds two more parameters)

$$\mu^l = \frac{1}{H}\sum_{i=1}^{H} a_i^l \qquad \sigma^l = \sqrt{\frac{1}{H}\sum_{i=1}^{H}\left(a_i^l - \mu^l\right)^2}$$

$$h_i = f\left(\frac{g_i}{\sigma_i}(a_i - \mu_i) + b_i\right)$$

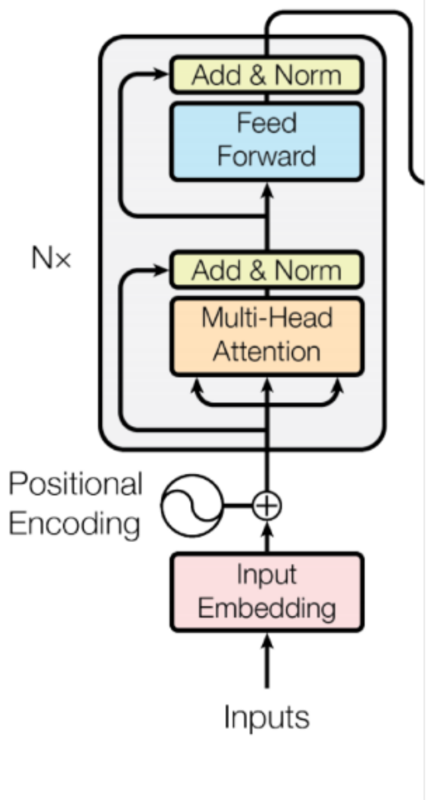
Transformer

Positional Encoding

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

Transformer Encoder

- For encoder, at each block, we use the same Q, K and V from the previous layer
- Blocks are repeated 6 times
  - (in vertical stack)



-> BERT, GPT 에 사용되는 Block

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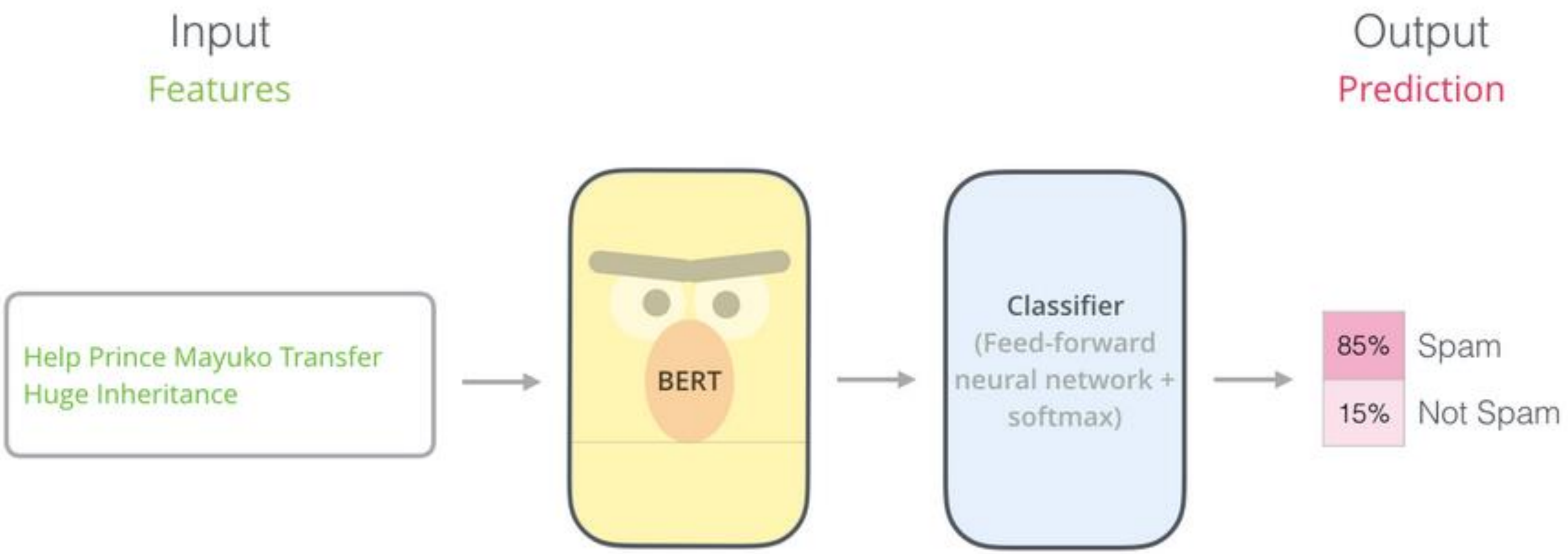
BERT

BERT : Bidirectional Encoder Representations from Transformers

Pre-training of Deep Bidirectional Transformers for Language Understanding



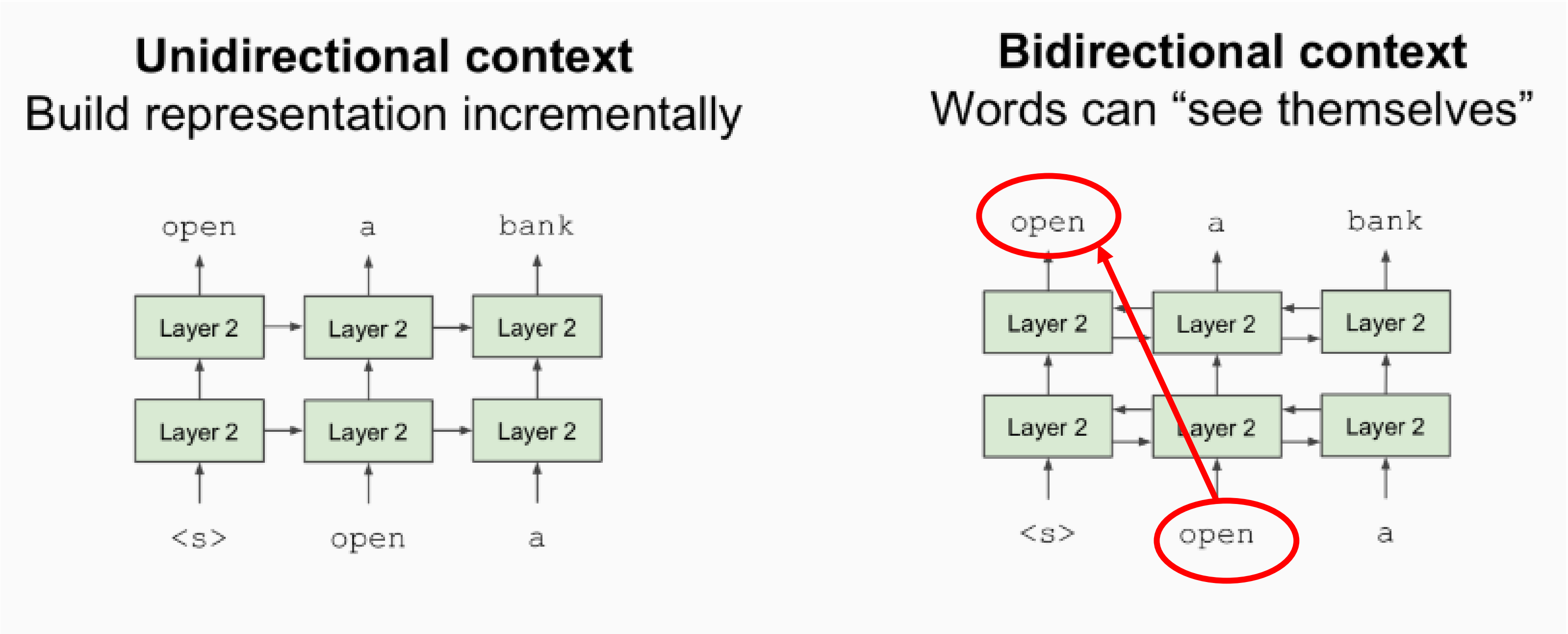
BERT

Problem) Language models only use left/right context, but language understanding is bidirectional

Why are LMs unidirectional?

Reason 1 : Directionality is needed to generate a well-formed probability distribution

Reason2 : Words can “see themselves” in a bidirectional encoder



BERT

Solution) Mask out k% of input words, and then predict the masked words

- They always use k = 15%

store ↑ gallon ↑

the man went to the [MASK] to buy a [MASK] of milk

Too little masking : Too expensive to train

Too much masking : Not enough context

BERT

Maksed LM (MLM)

Solution) Mask out k% of input words, and then predict the masked words

- They always use *k* = 15%

store ↑ gallon ↑

the man went to the [MASK] to buy a [MASK] of milk

Too little masking : Too expensive to train

Too much masking : Not enough context

BERT

Next Sentence Prediction (NSP)

To learn relationships between sentences, predict whether sentence B is actual sentence

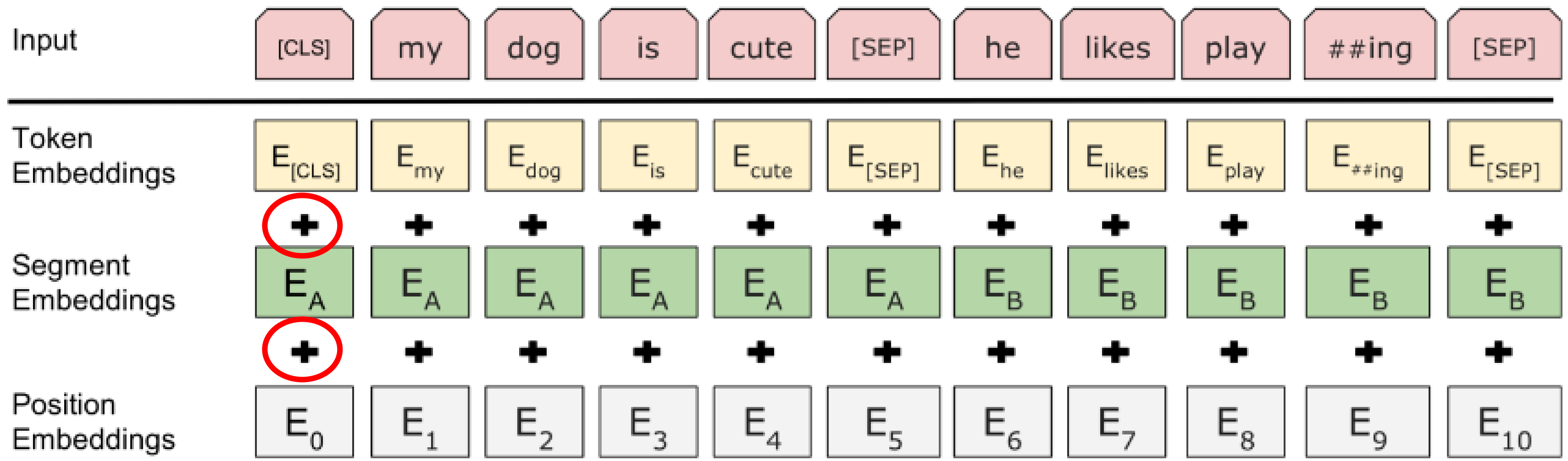
thar proceeds sentence A, or a random sentence

Sentence A = `The man went to the store.`
Sentence B = `He bought a gallon of milk.`
Label = `IsNextSentence`

Sentence A = `The man went to the store.`
Sentence B = `Penguins are flightless.`
Label = `NotNextSentence`

BERT

Input representation - sentence pair encoding



use summed representation

token Embedding : word piece

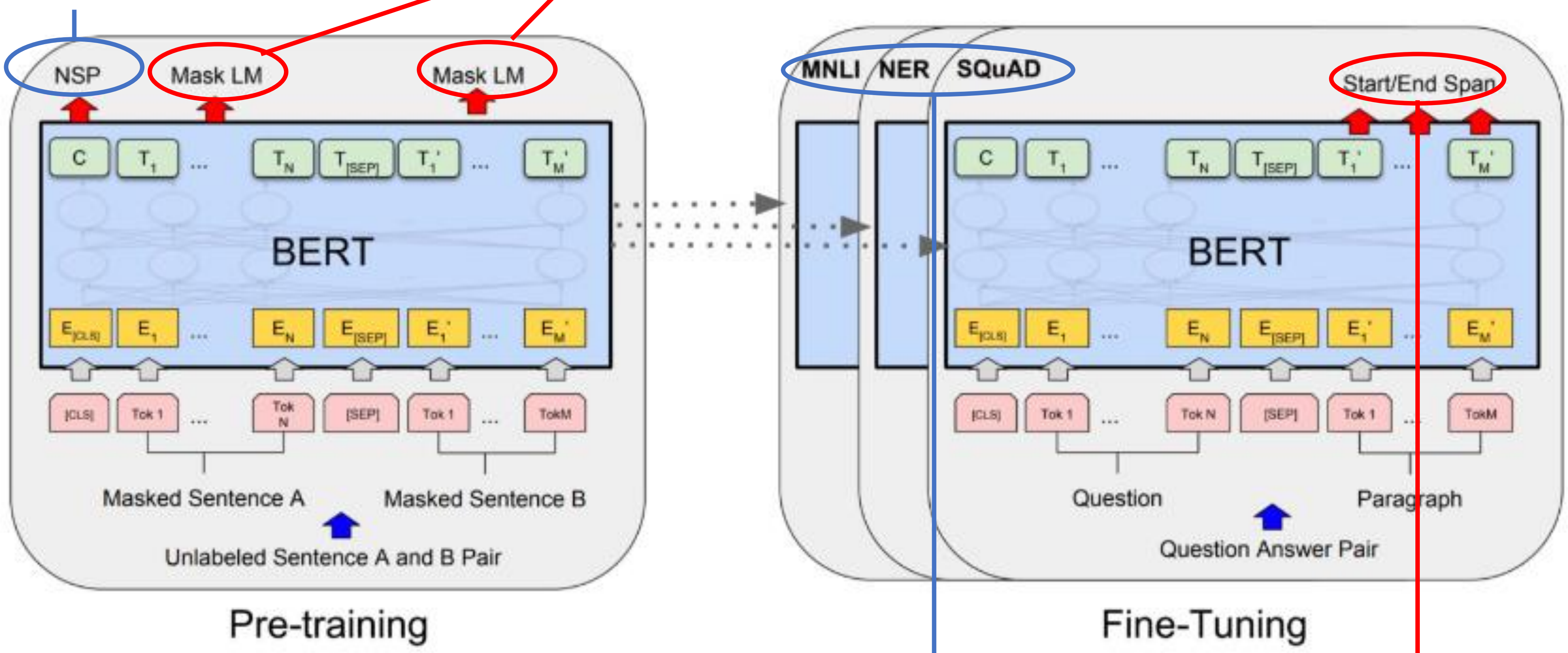
segment Embedding : for each word piece whether it comes from the first/second sentence before/after the separator

Positional Embedding : for other Transformer architectures

BERT

binary prediction function as to whether a correct next sentence or not

losses to extent that you can't predict the masked words



useful for various tasks

substitute with a final prediction layer

BERT

Train 2 model sizes:

BERT-Base : 12-layer, 12-head, 768-hidden

BERT-Large : 24-layer, 1024-hidden, 16-head

Use transformer encoder

- self-attention => no locality bias
- single multiplication per layer => efficiency on GPU/TPU

BERT

transformer encoder