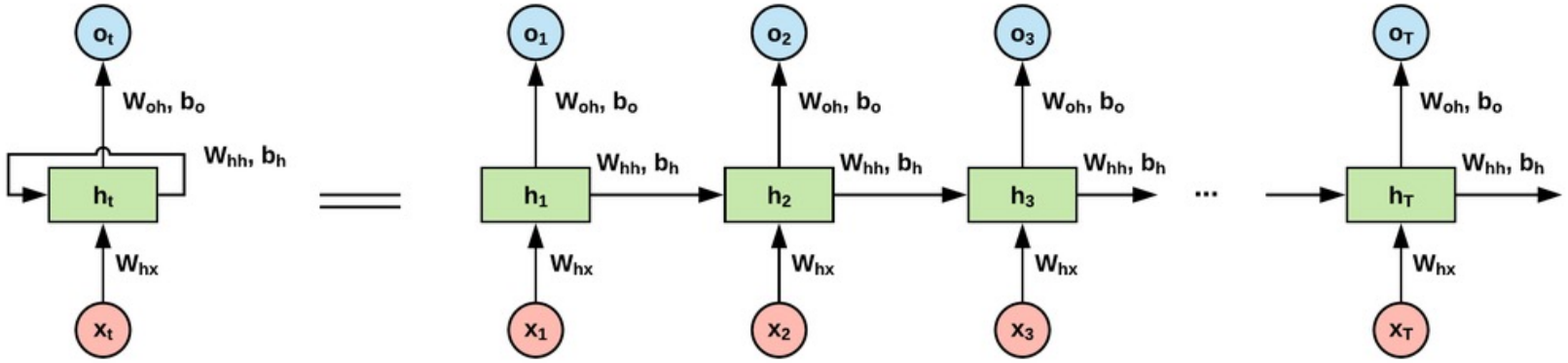
Attention Is All You Need

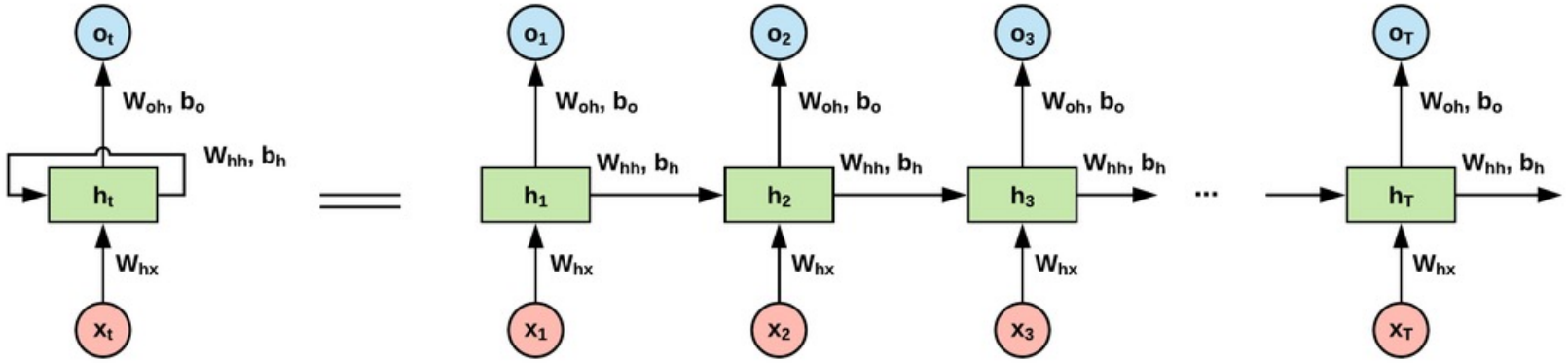
4기 물리학과 이윤영

RNN



Sequential data 처리에 용이한 neural network

RNN

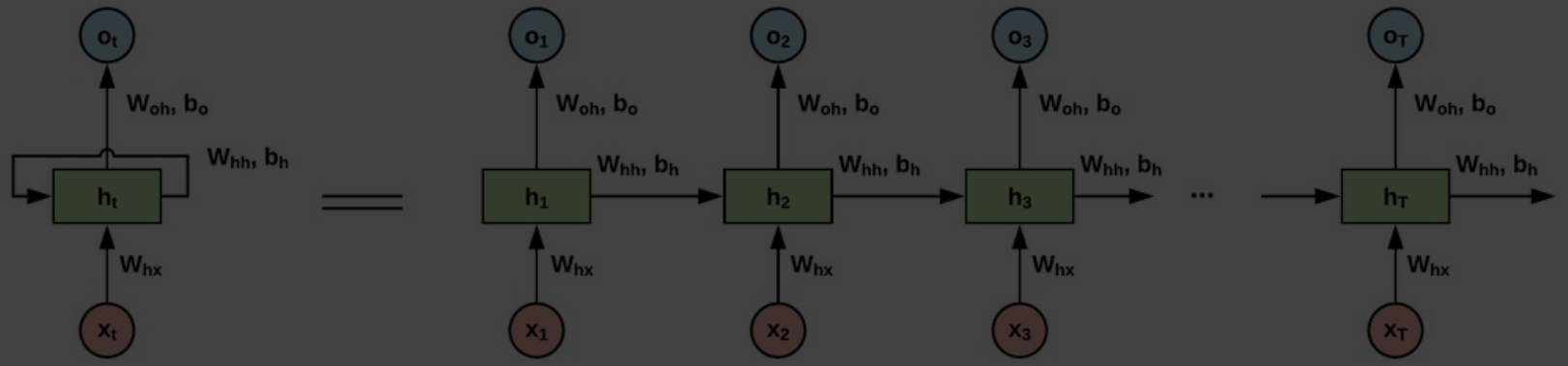


Sequential data 처리에 용이한 neural network

↓

Time step 별로 data를 처리!

RNN



Sequential data 처리에 용이한 neural network

↓

Time step 별로 data를 처리!

Data의 병렬처리 어려움 -> 긴 sequence에서 효과적이지 않음!

TRANSFORMER!

TRANSFORMER!

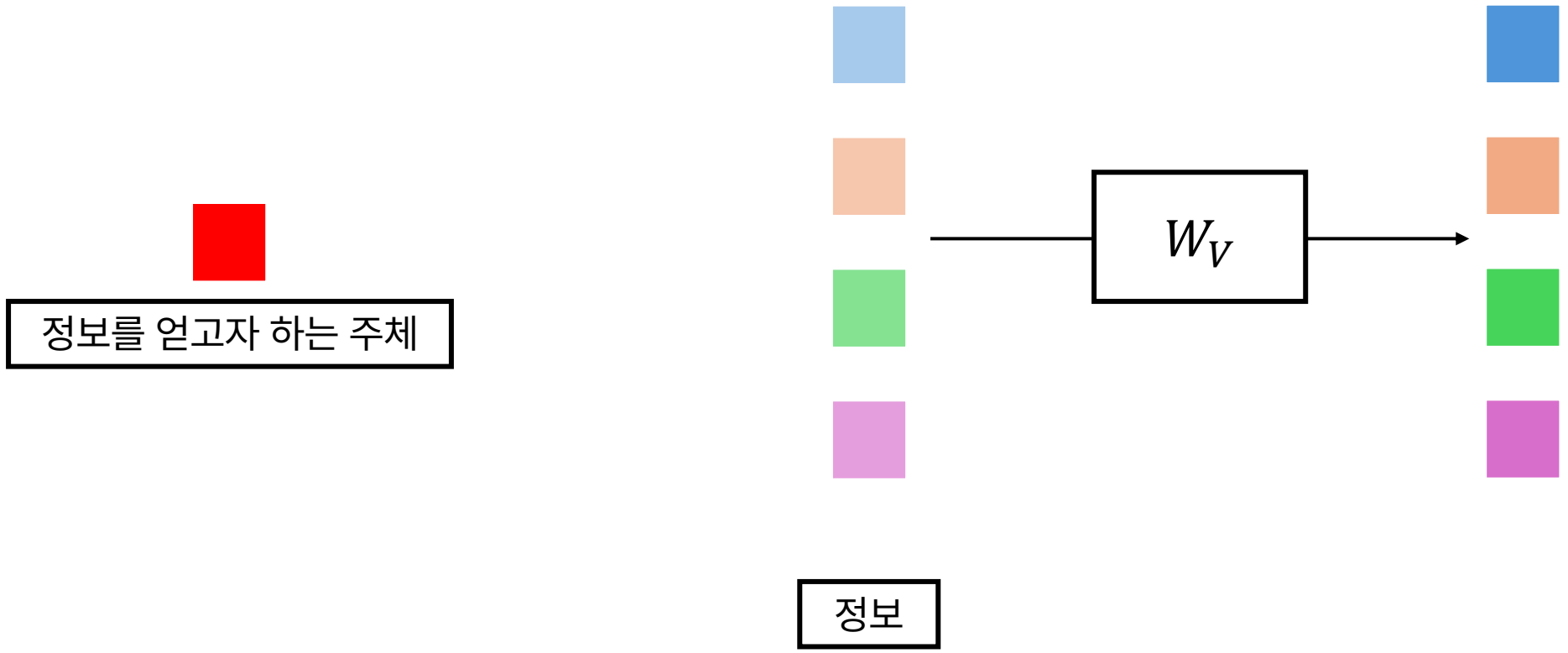
Attention Is All You Need

TRANSFORMER!

Attention Is All You Need

Successfully reduce RNN, CNN

What is attention?



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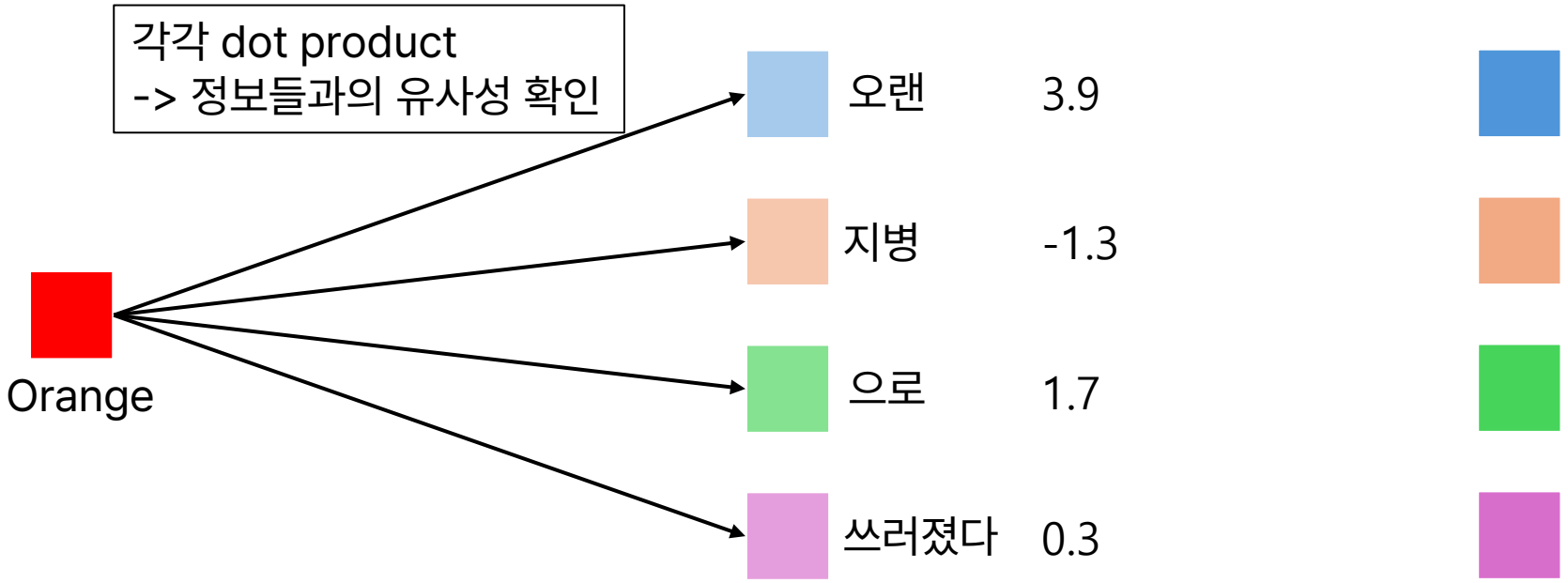
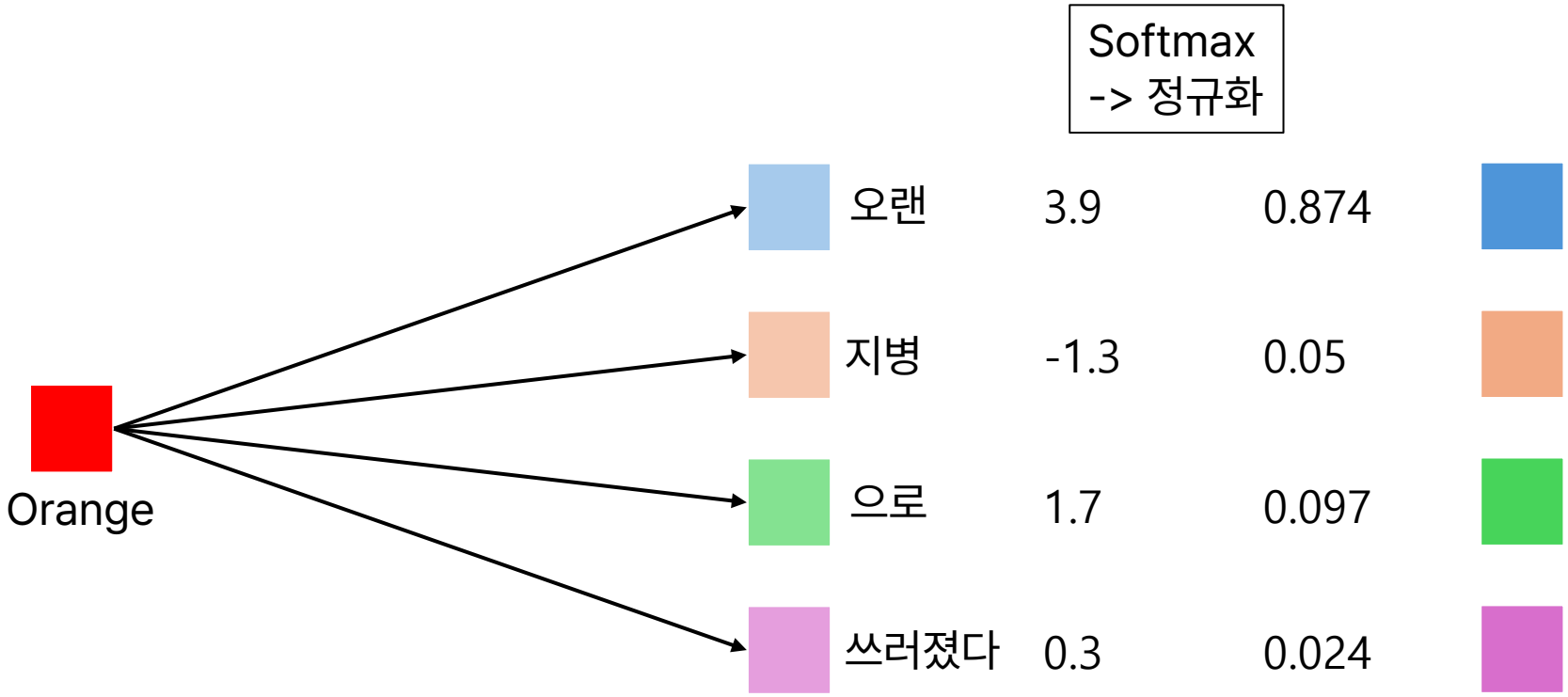


Query

Key

Value

What is attention?



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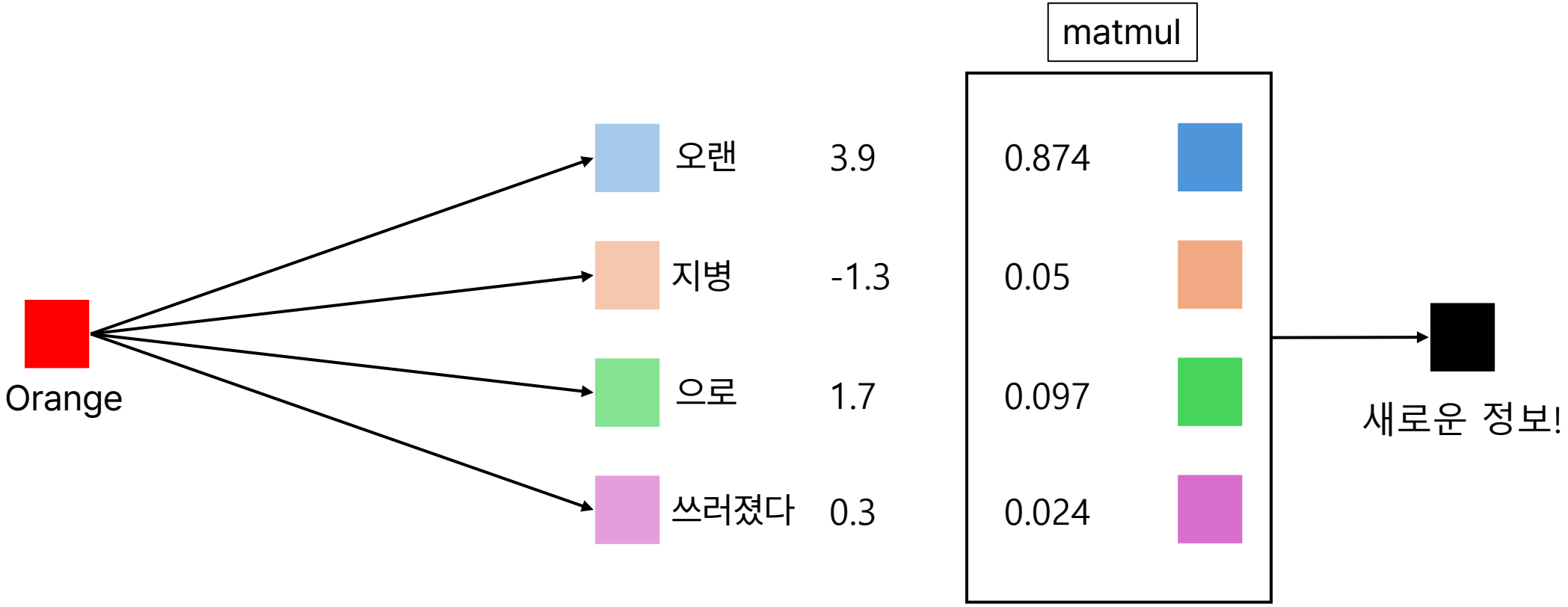

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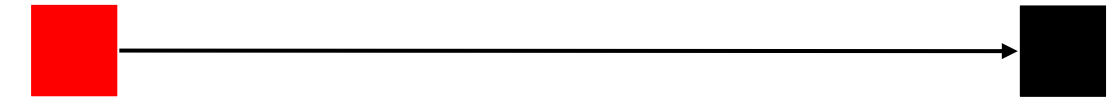


각 key값들의 정보가 포함된 새로운 정보

What is attention?

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

What is attention?

Query, Keys, Values

Scale dot product

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

Sqrt of keys vector dimension
-> To prevent increasing dot product

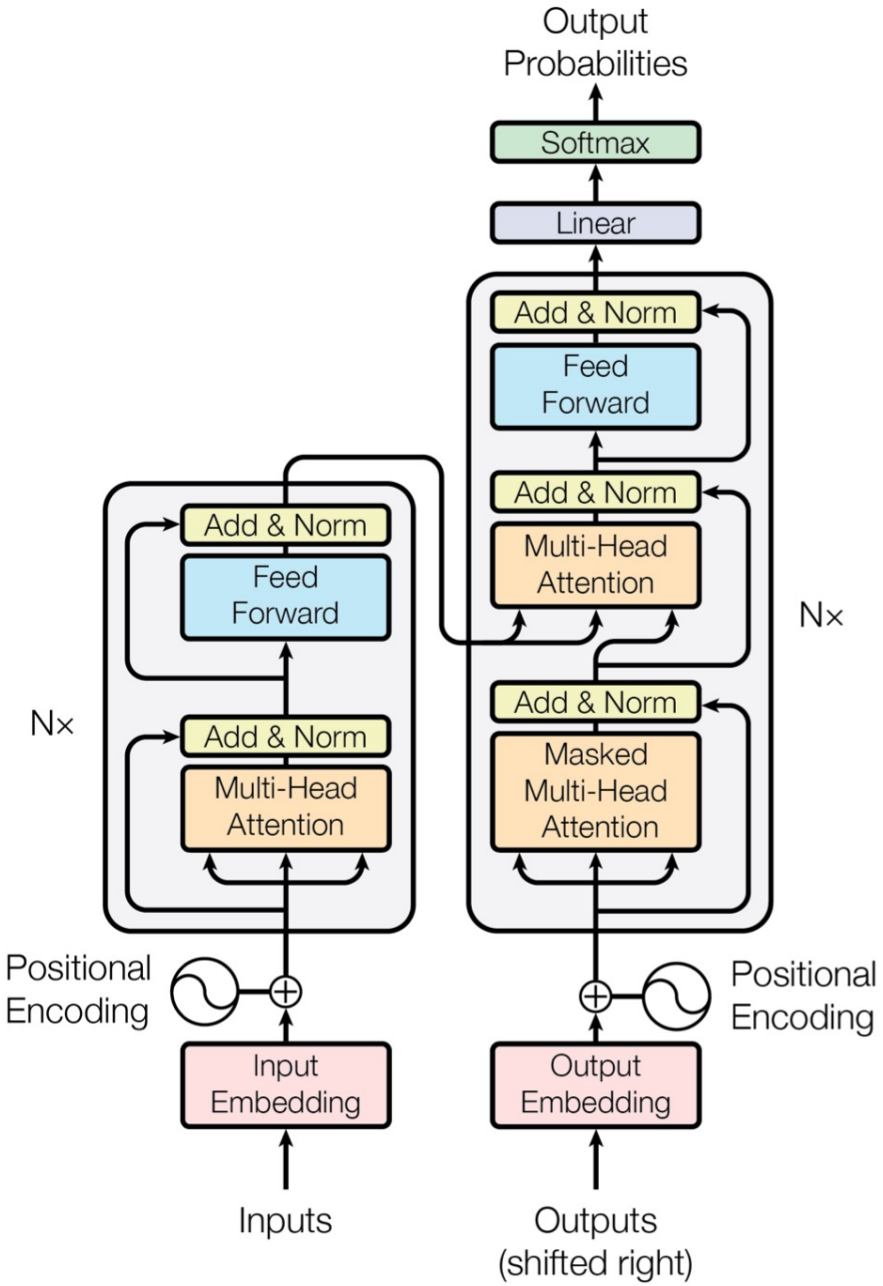
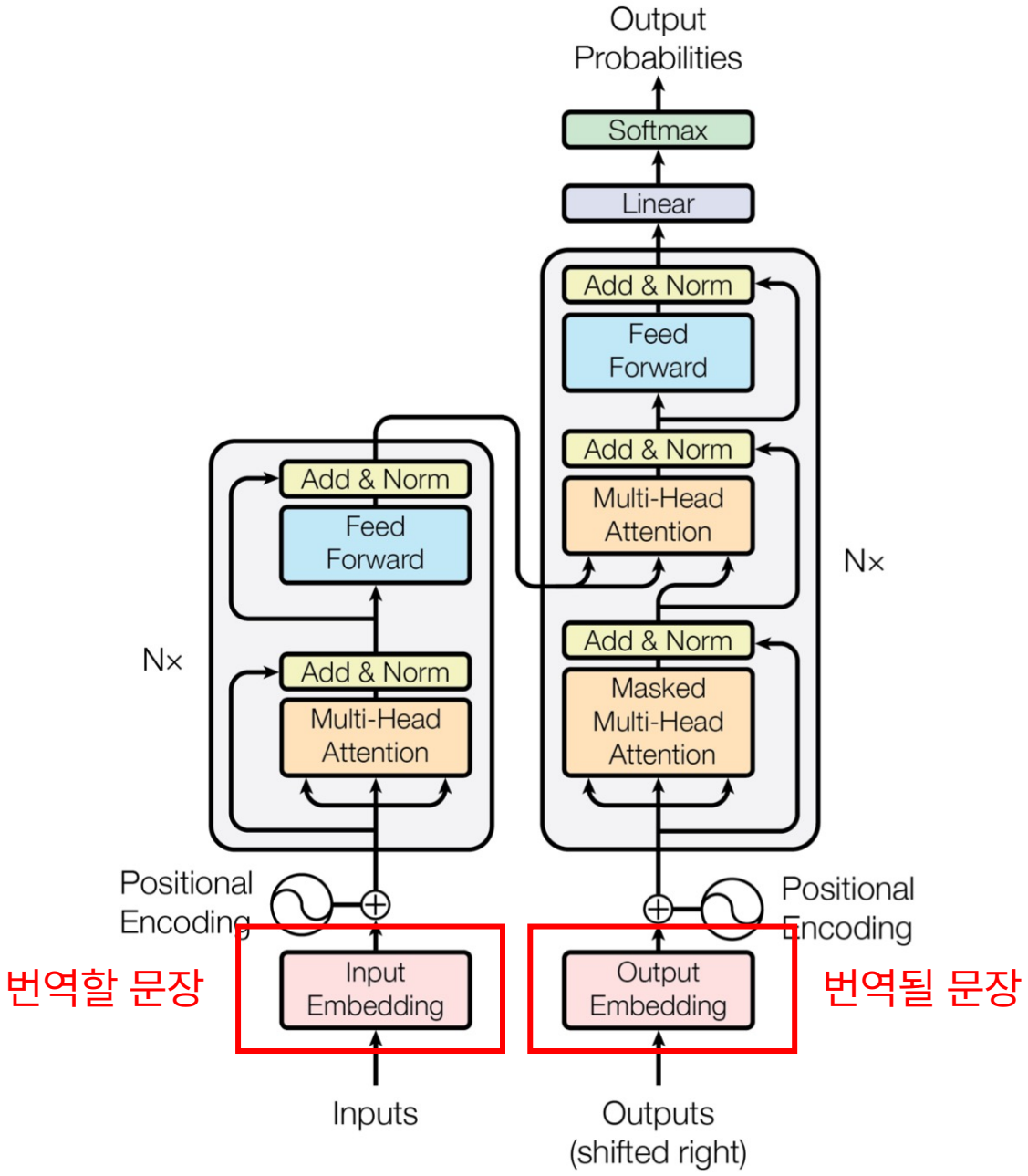


Figure 1: The Transformer - model architecture.



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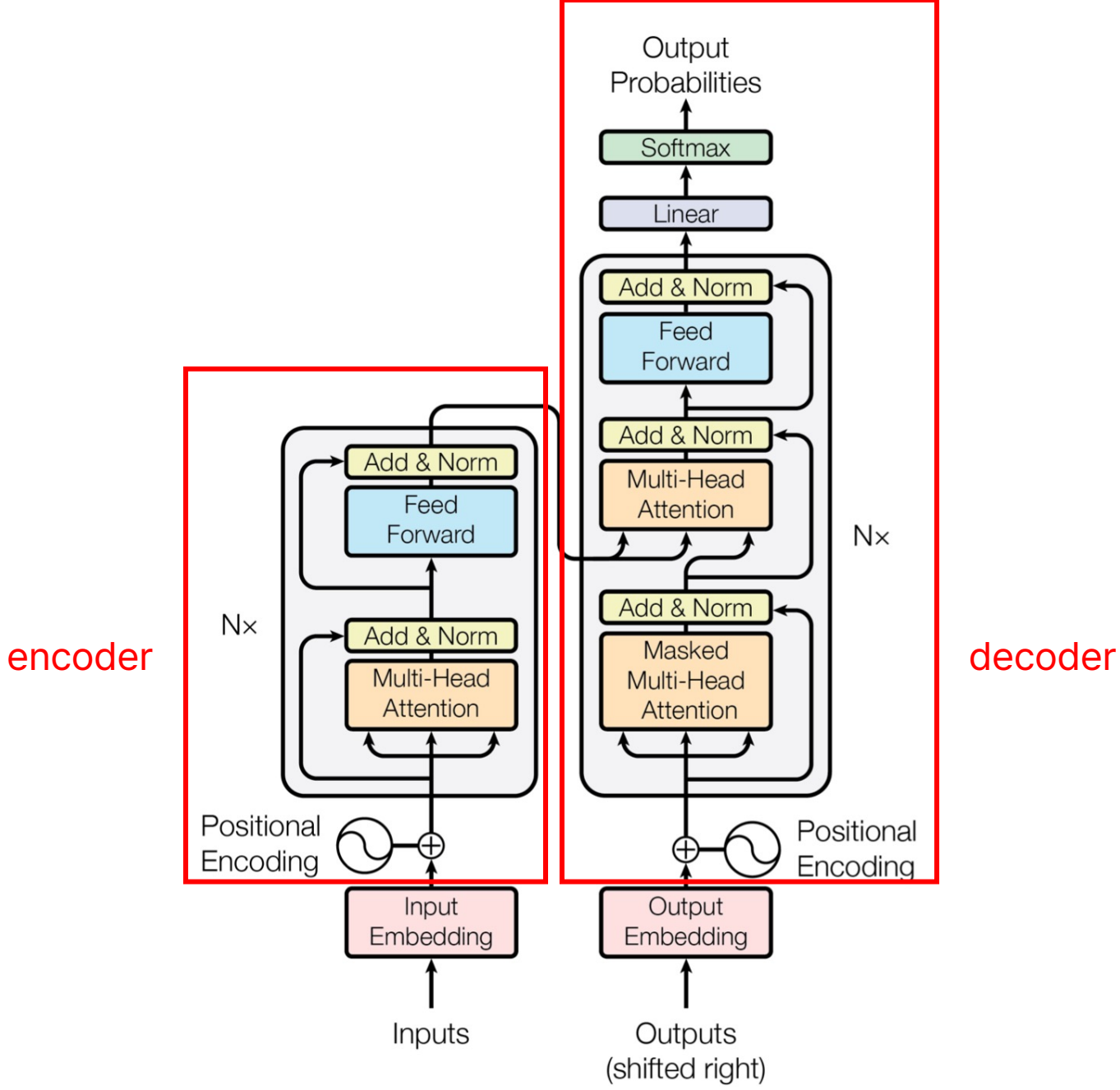

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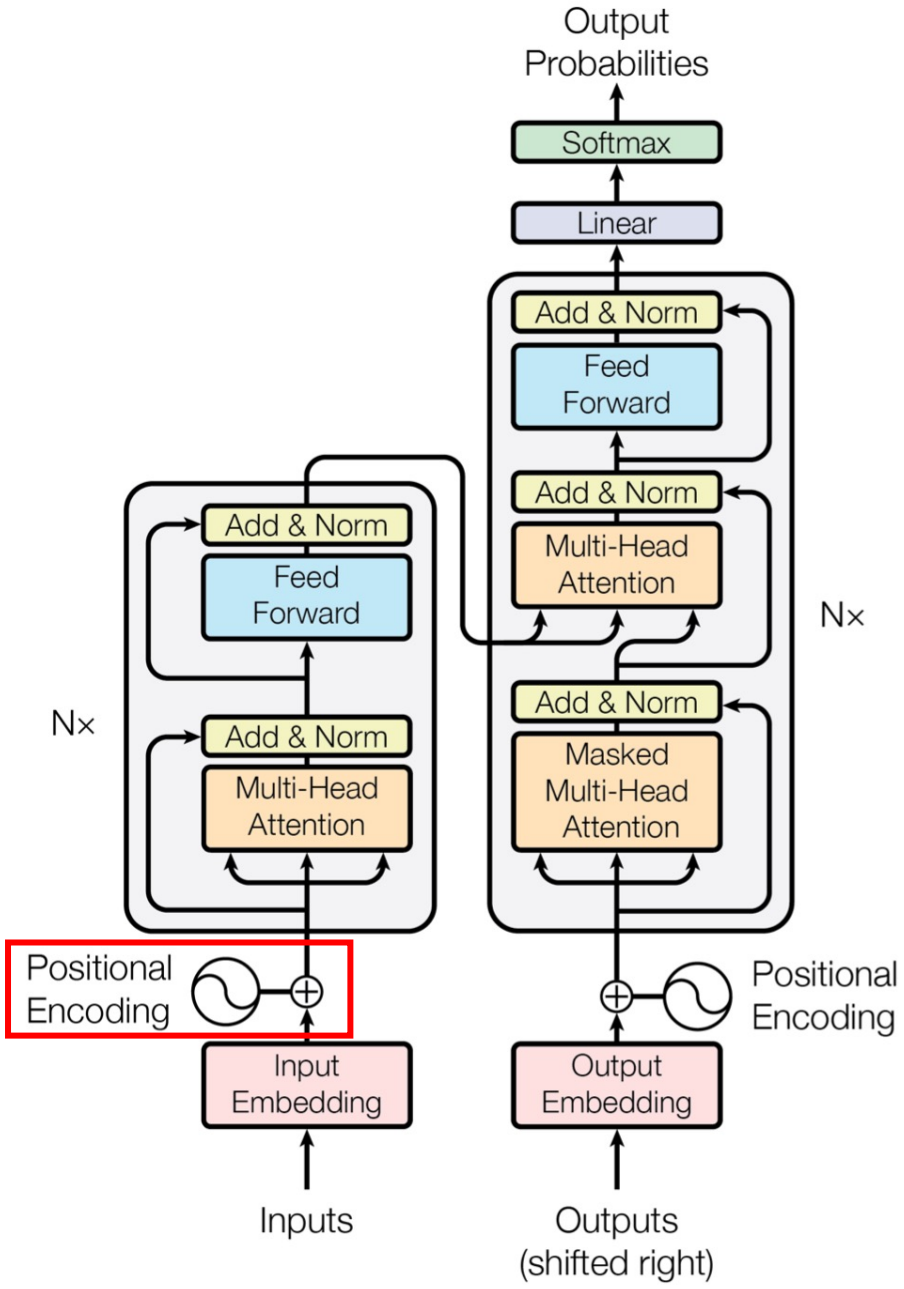
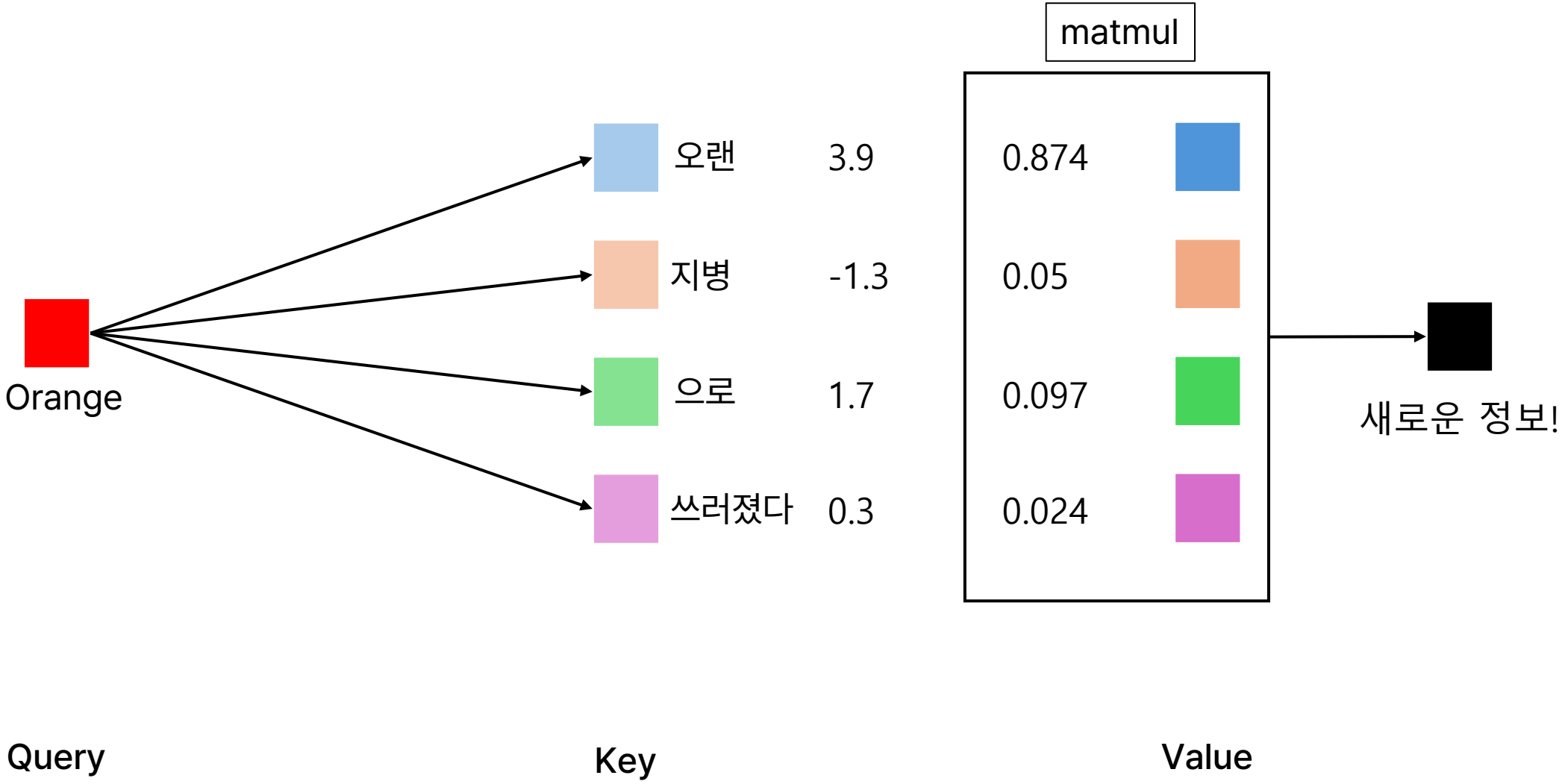


Figure 1: The Transformer - model architecture.

1. Positional Encoding



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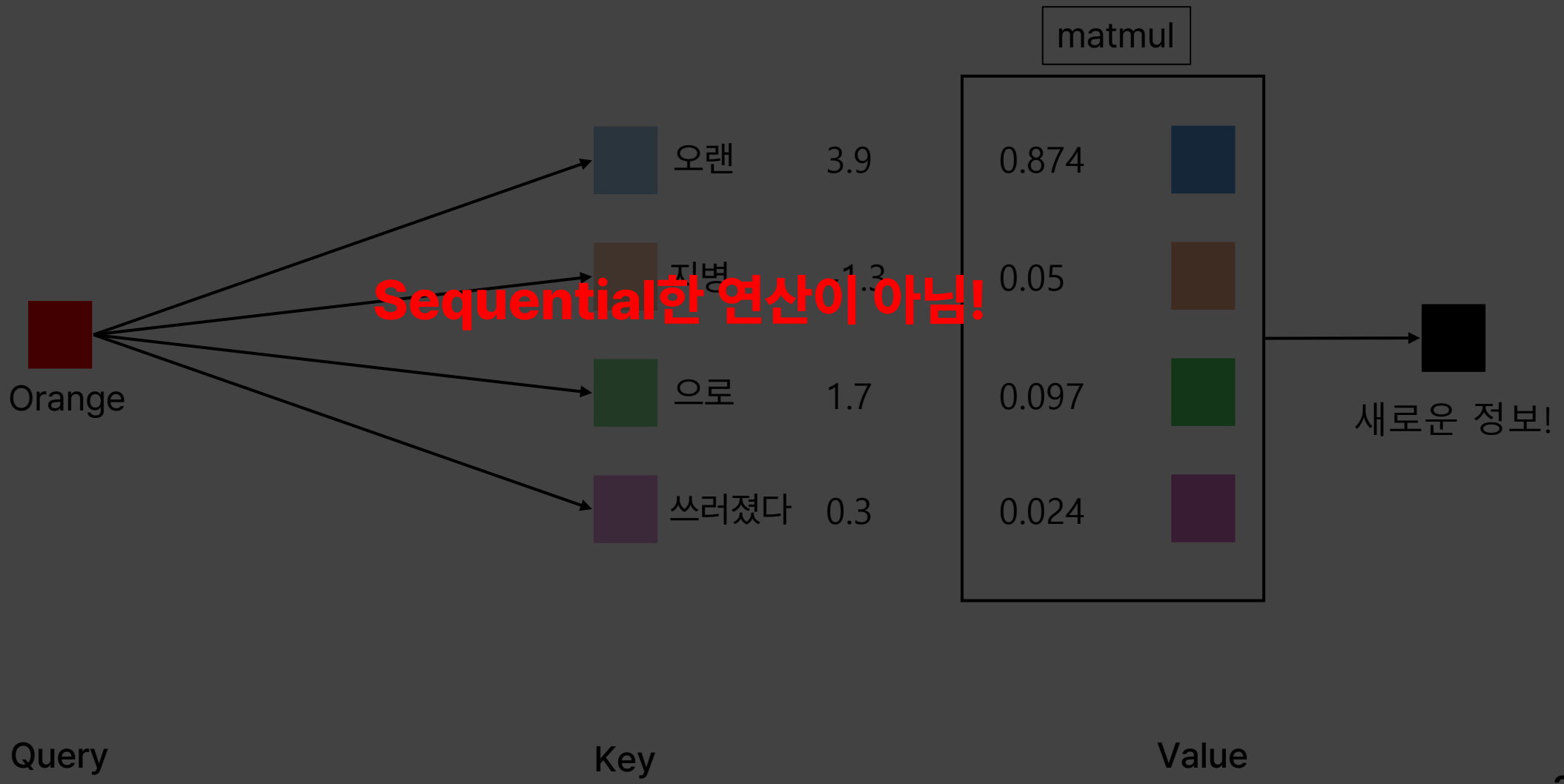
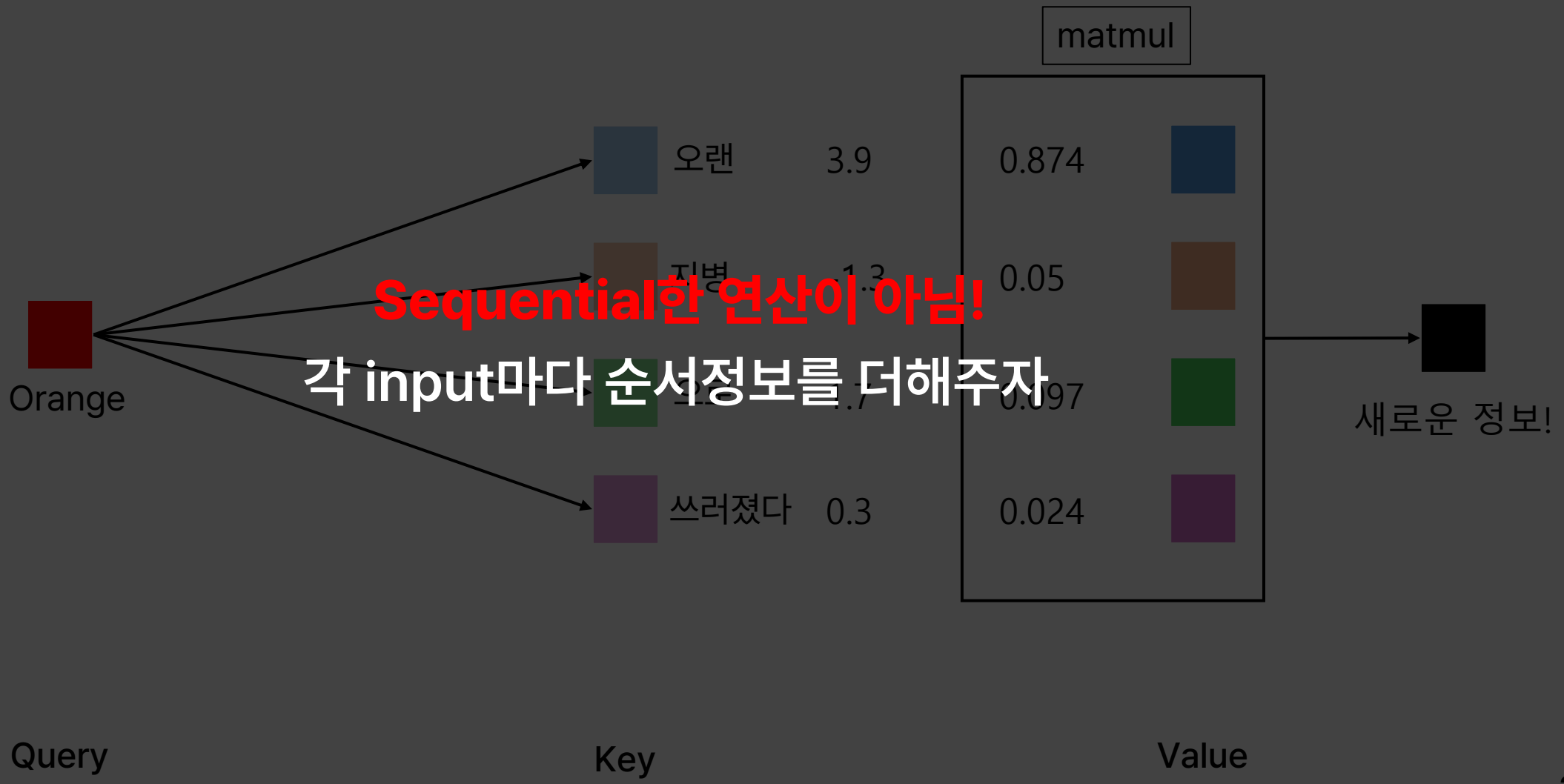


1. Positional Encoding



1. Positional Encoding

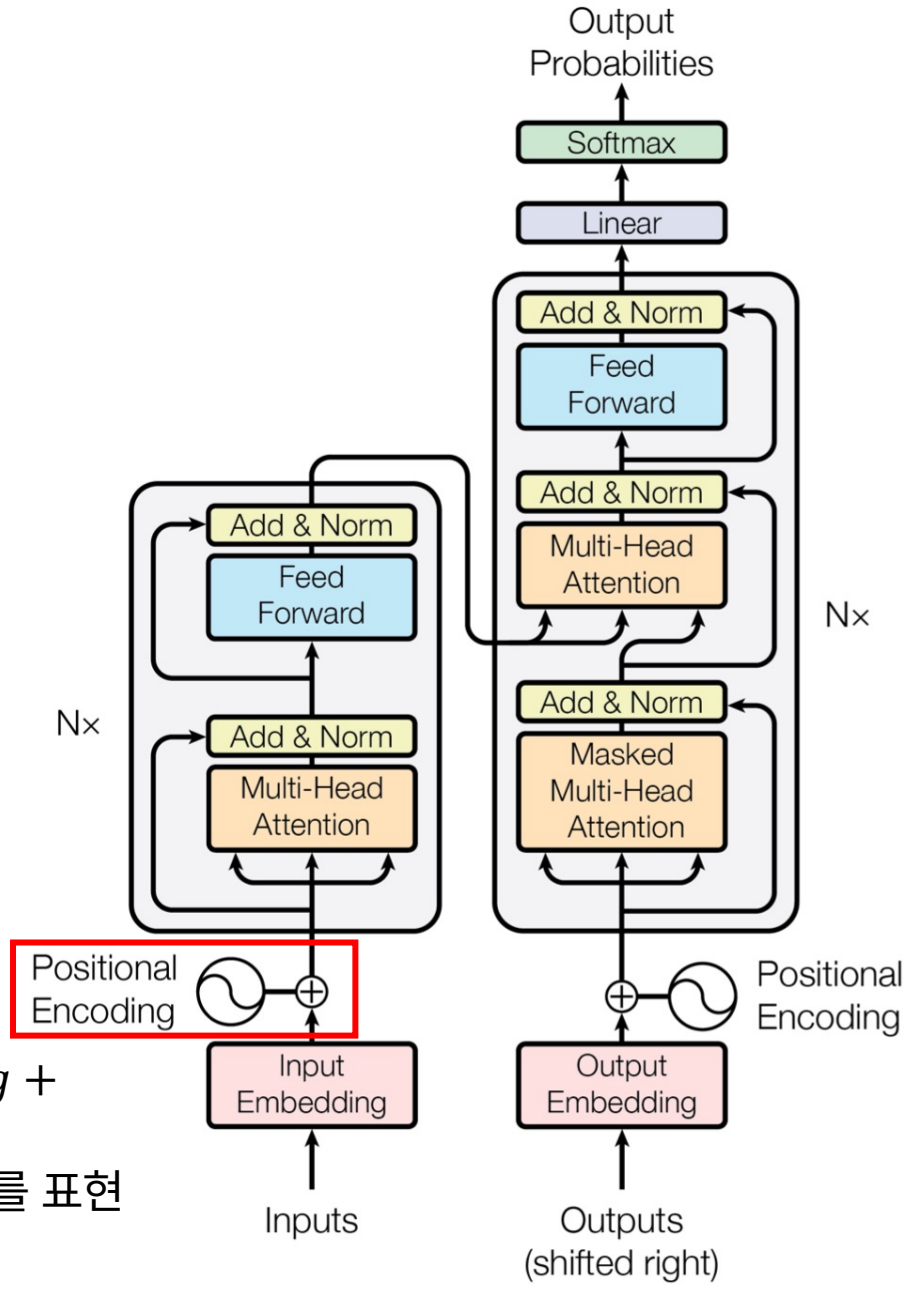
pos : input 순서
i : vector 내의 차원 index

Model dimension

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

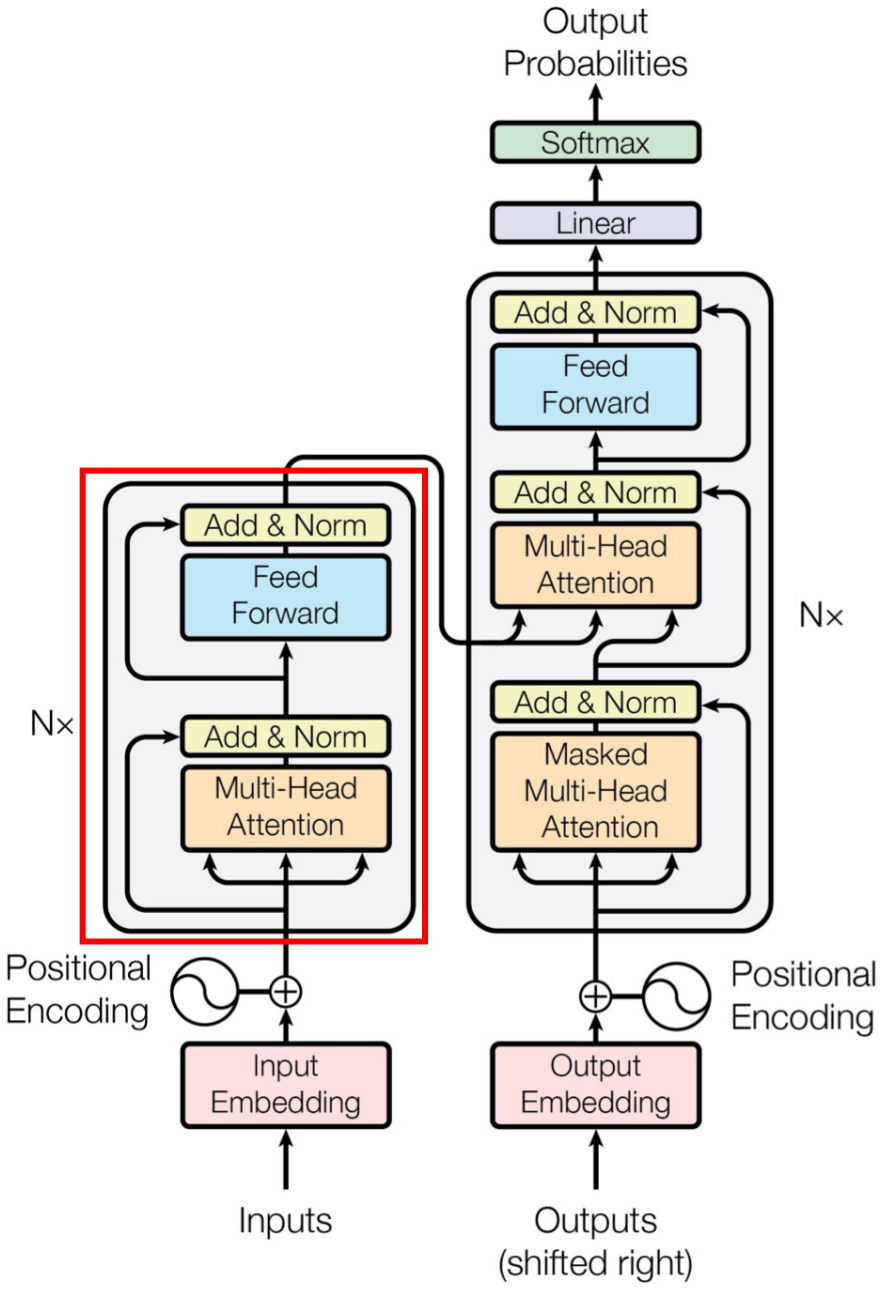
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

1. 주기함수의 주기성
   - pos의 차이가 커질 수록 PE차이가 커짐
   - pos의 상대적인 차이가 같다면 PE차이가 같음
   -> 순서정보에 적합!
2. 10000?
   - Input sequence의 현실적인 최대길이?
   - 적절한 분해능?
     - 10000보다 작으면 : 서로 다른 위치가 유사한 값을 가질수도
     - 10000보다 크면 : 인코딩간 차이가 너무 작아져 분별력이 떨어질수도
     - 아마 실험적인 결과가 아닐까



1. $Inputs = Word\ Embadding + Positional\ Encoding$
2. PE는 sinsoid함수로 순서정보를 표현

Figure 1: The Transformer - model architecture.



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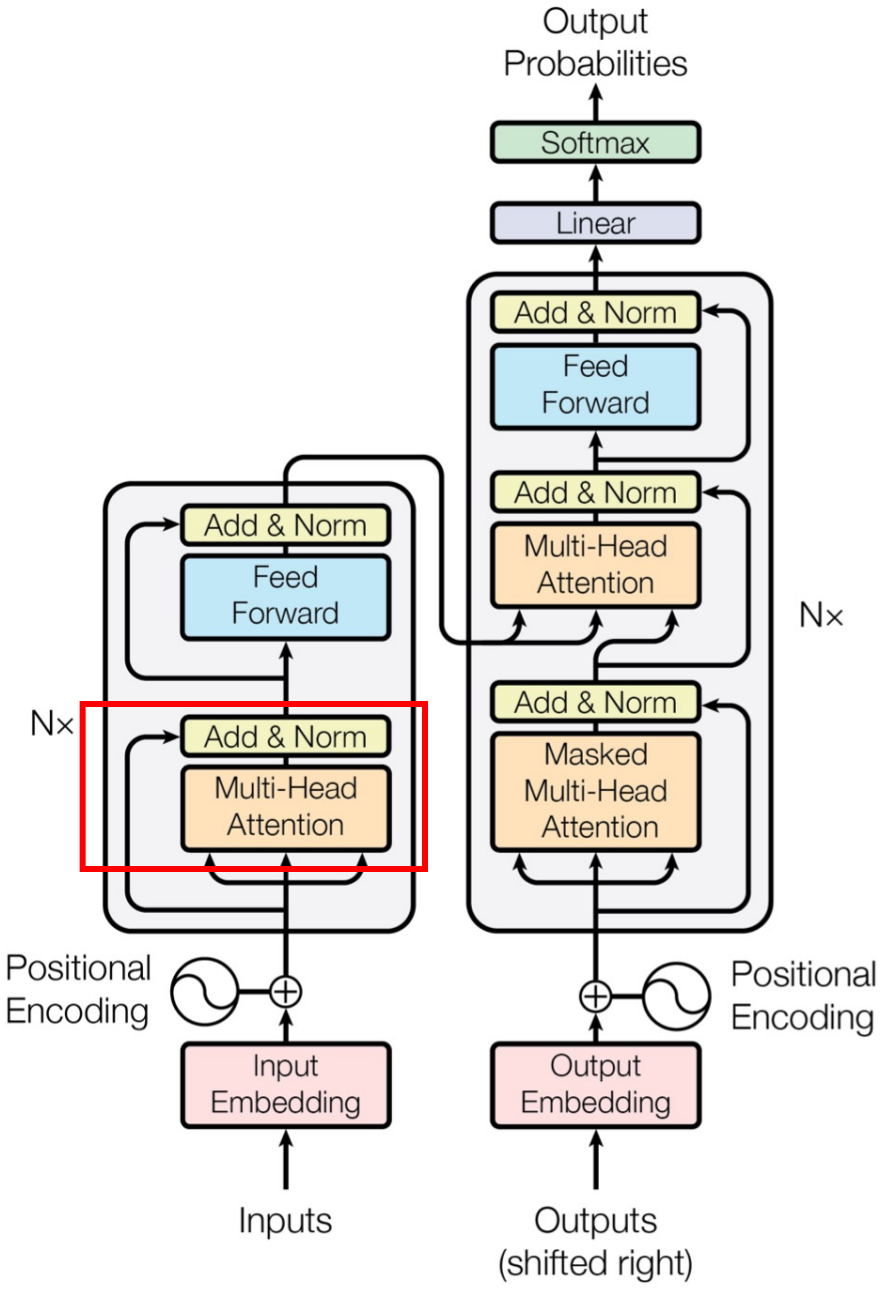

Figure 1: The Transformer - model architecture.

2. Multi-head attention

인도 음식점에 가던 중 주행 금지 표지판을 보았다

인도 주행 금지 표지판을 음식점에 가던 중 보았다

2. Multi-head attention

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동음이의어
But, 둘 다 첫번째 순서인데?

2. Multi-head attention

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동음이의어

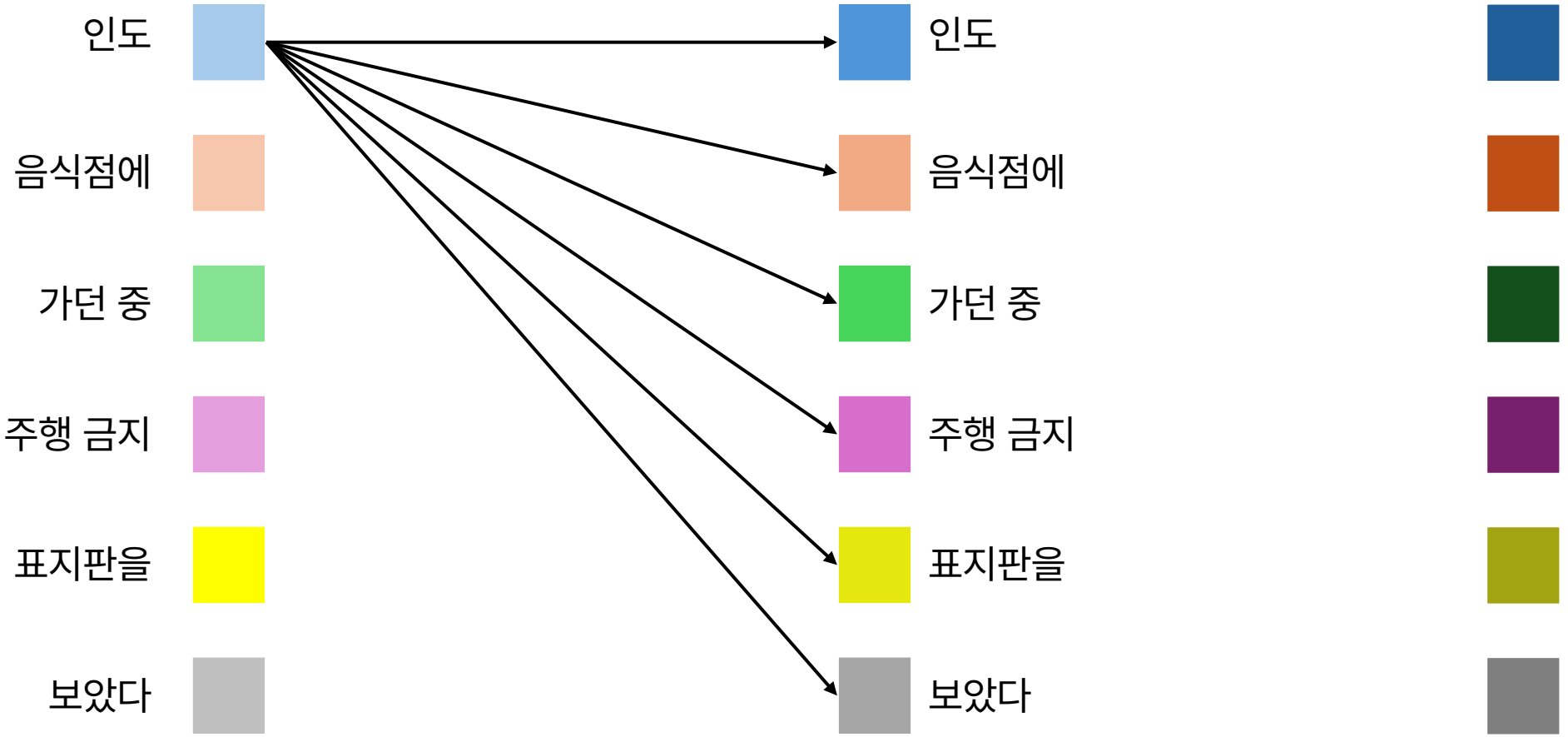
But, 둘 다 첫번째 순서인데?

주변 단어들을 통해 맥락을 확인하자

2. Multi-head attention

Self Attention

2. Multi-head attention – self attention



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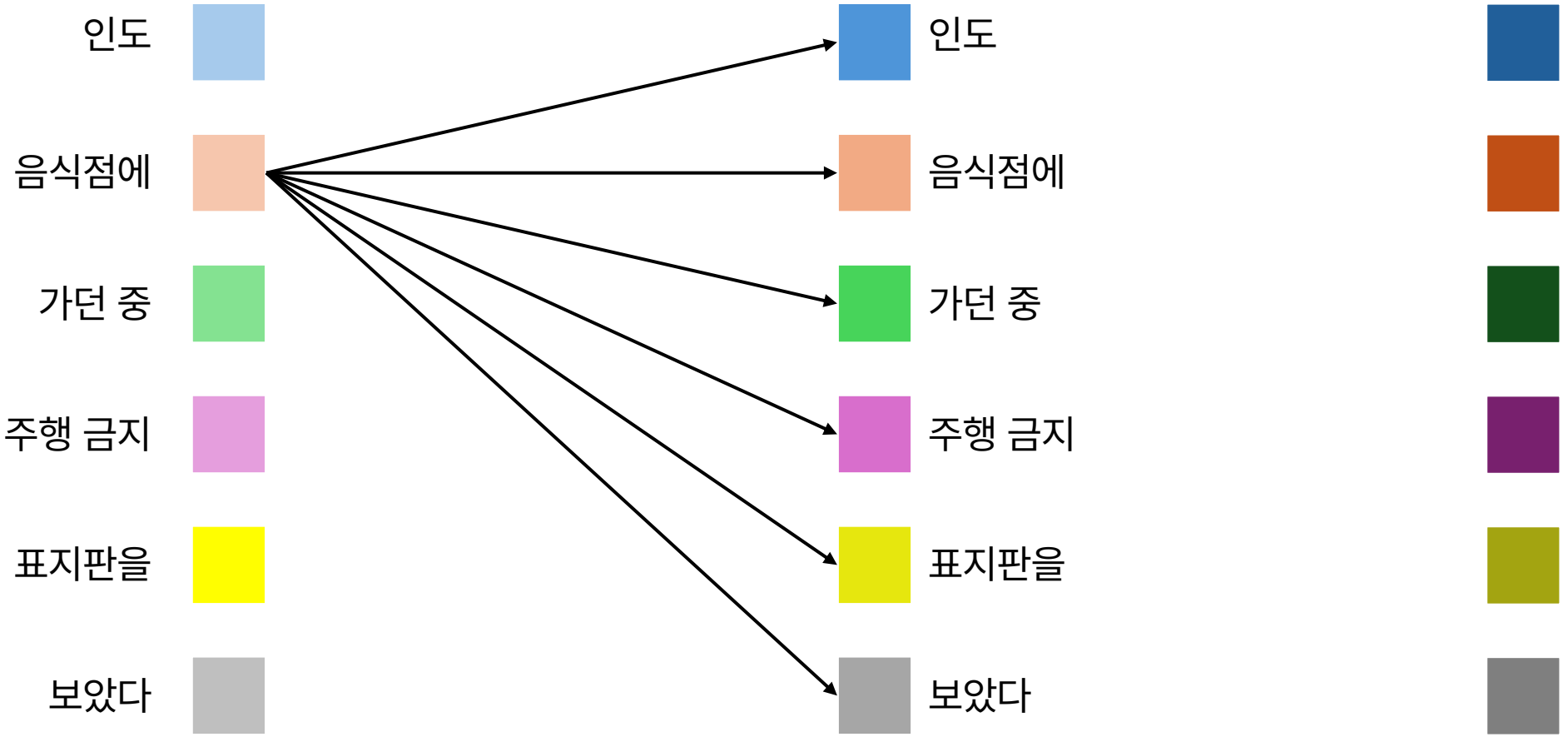

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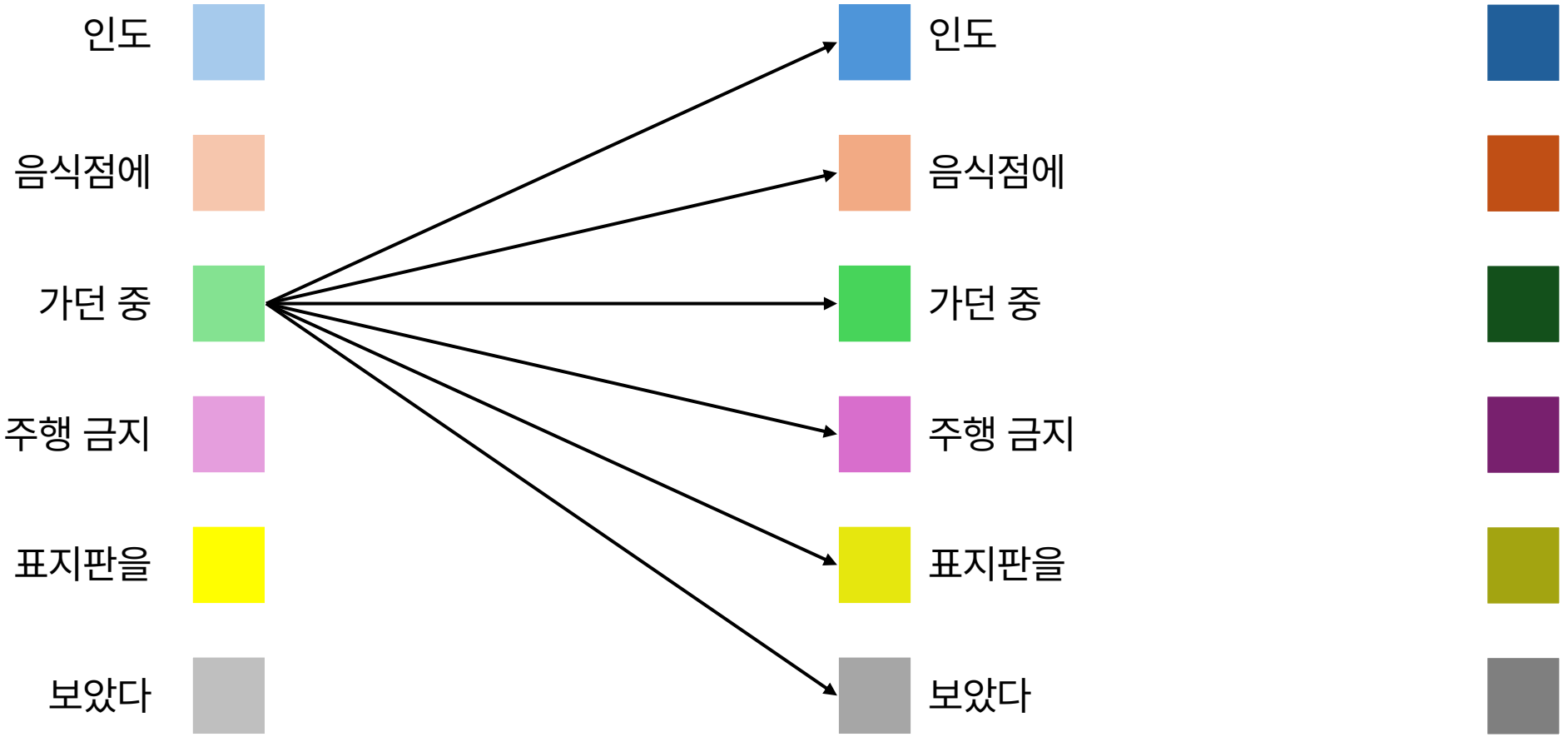


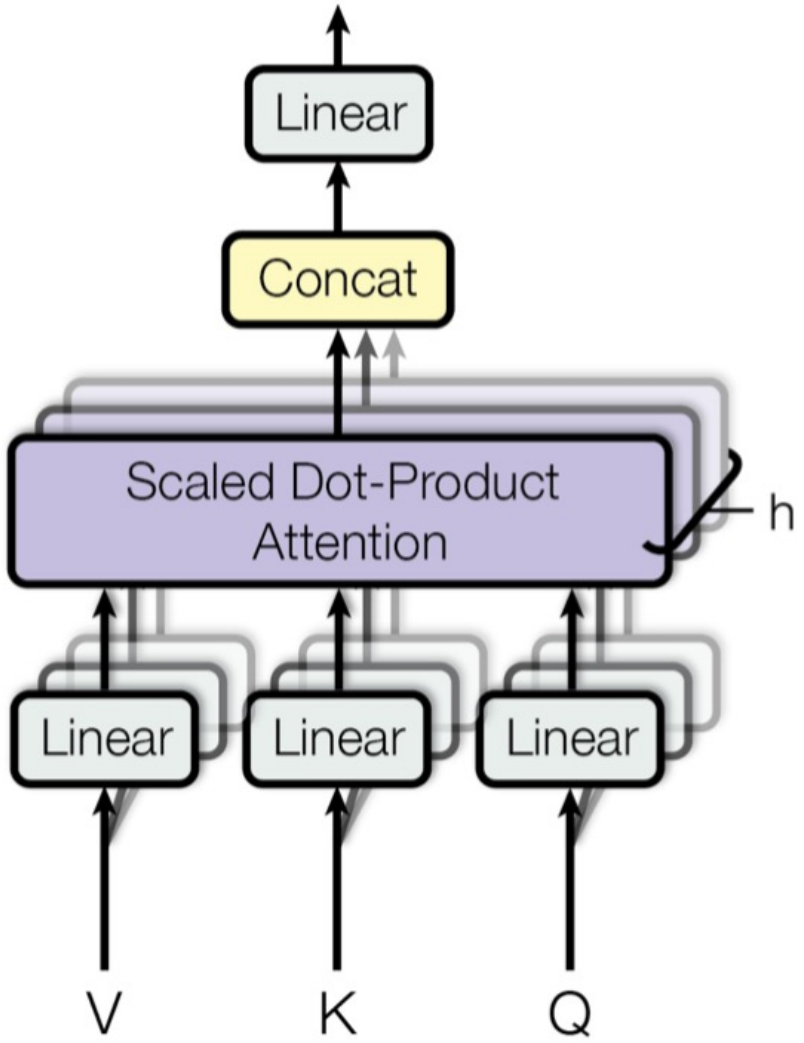
2. Multi-head attention

Self Attention : 자기 자신과 attention 연산을 하는 것

2. Multi-head attention

Multi-head Attention : self attention을 한 번에 병렬처리 하여 연산하는 것

2. Multi-head attention



h=8

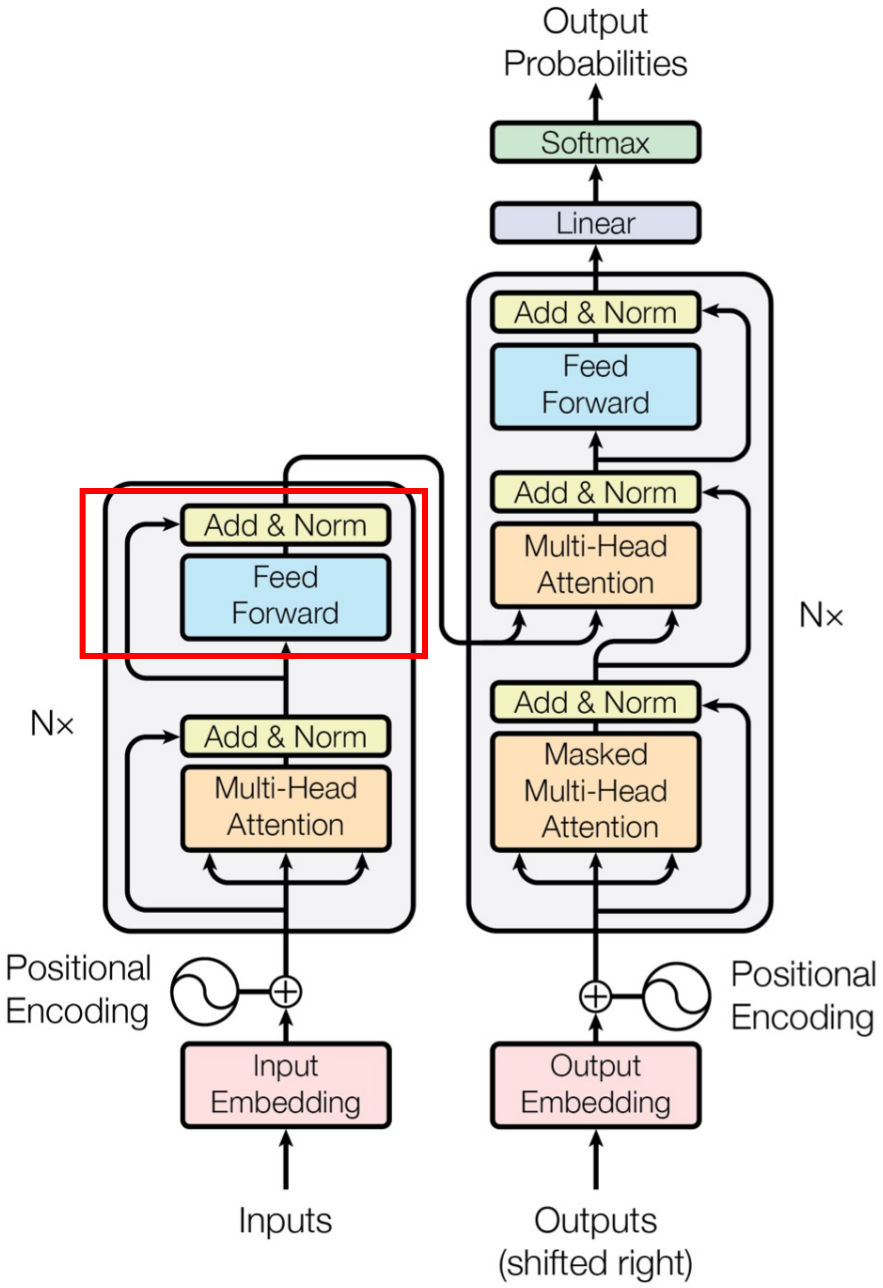


Figure 1: The Transformer - model architecture.

3. Feed Forward

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

2. ReLU

1. fully connected layer

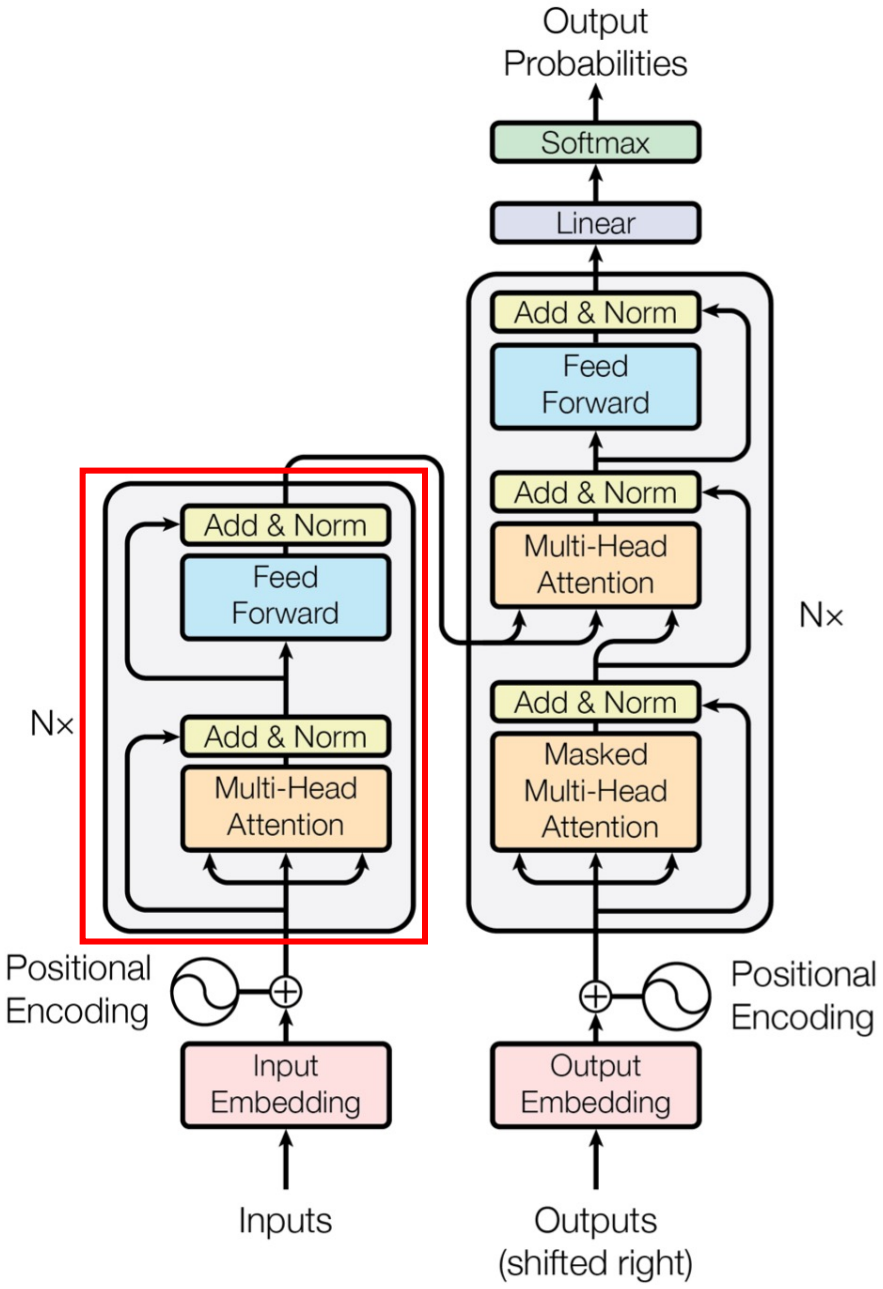
3. fully connected layer

-> 비선형성 부여!

N=6

Encoder의 input, output의 차원은 같다

input 문장으로 맥락이 포함된 단어 정보를 만듦



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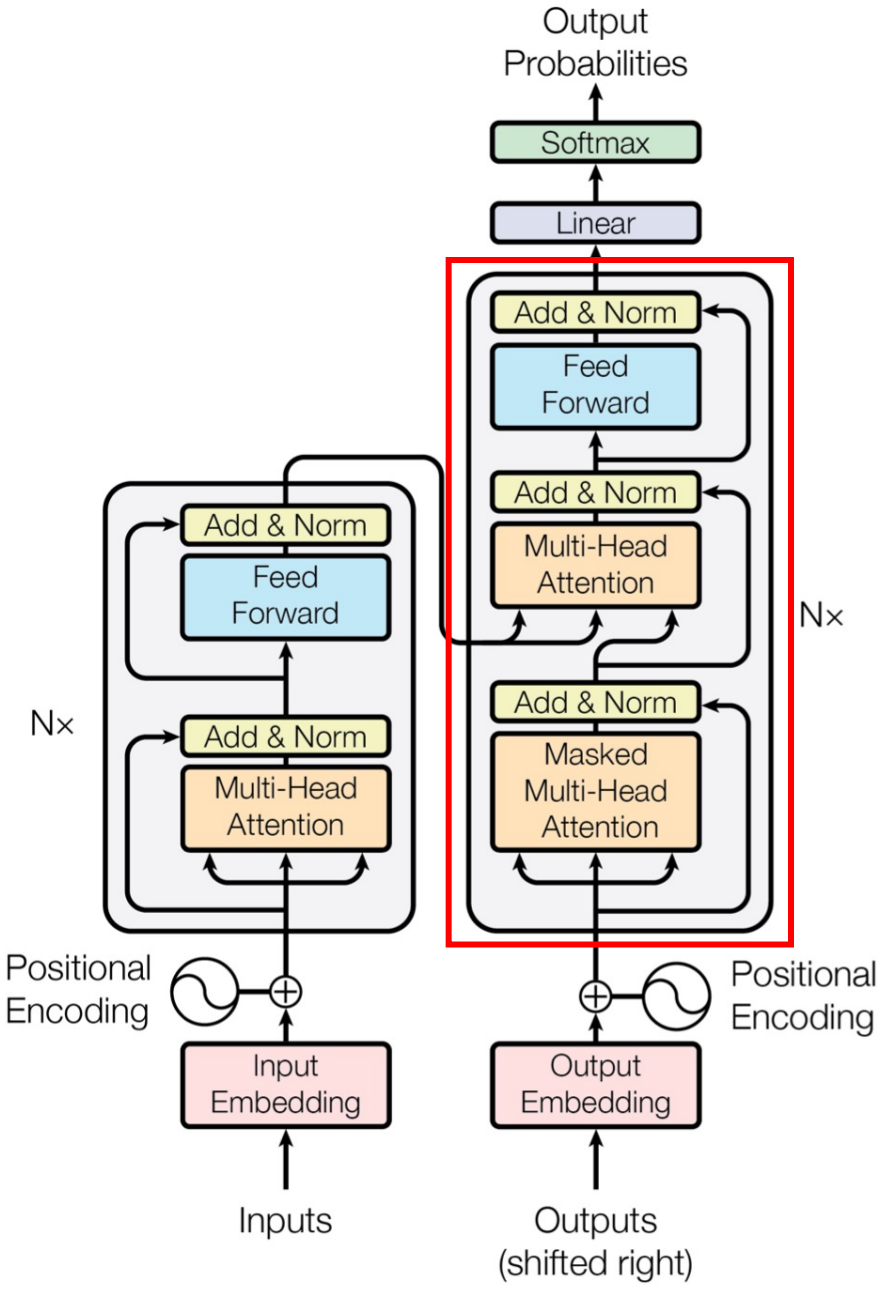

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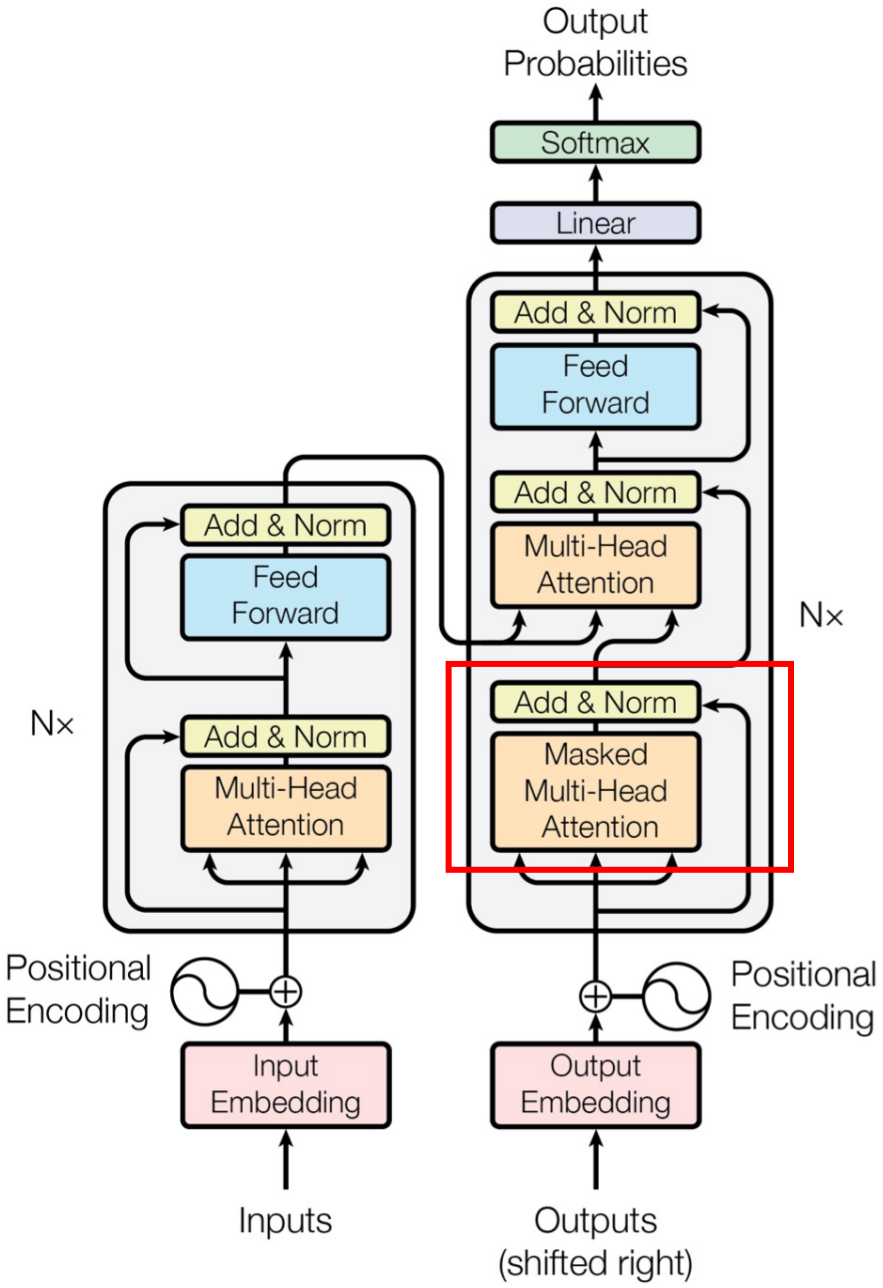

Figure 1: The Transformer - model architecture.

3. Masked Multi-head attention

아 자퇴하고 싶다

3. Masked Multi-head attention

아 (나는) 자퇴하고 싶다 ⟶ Oh, I want to quit my school

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아 (나는) 자퇴하고 싶다 ⟶ Oh, I want to **quit** my school

3. Masked Multi-head attention

아 (나는) 자퇴하고 싶다 ⟶ Oh, I want to quit my school

3. Masked Multi-head attention

아 (나는) 자퇴하고 싶다 → Oh, I want to quit my school

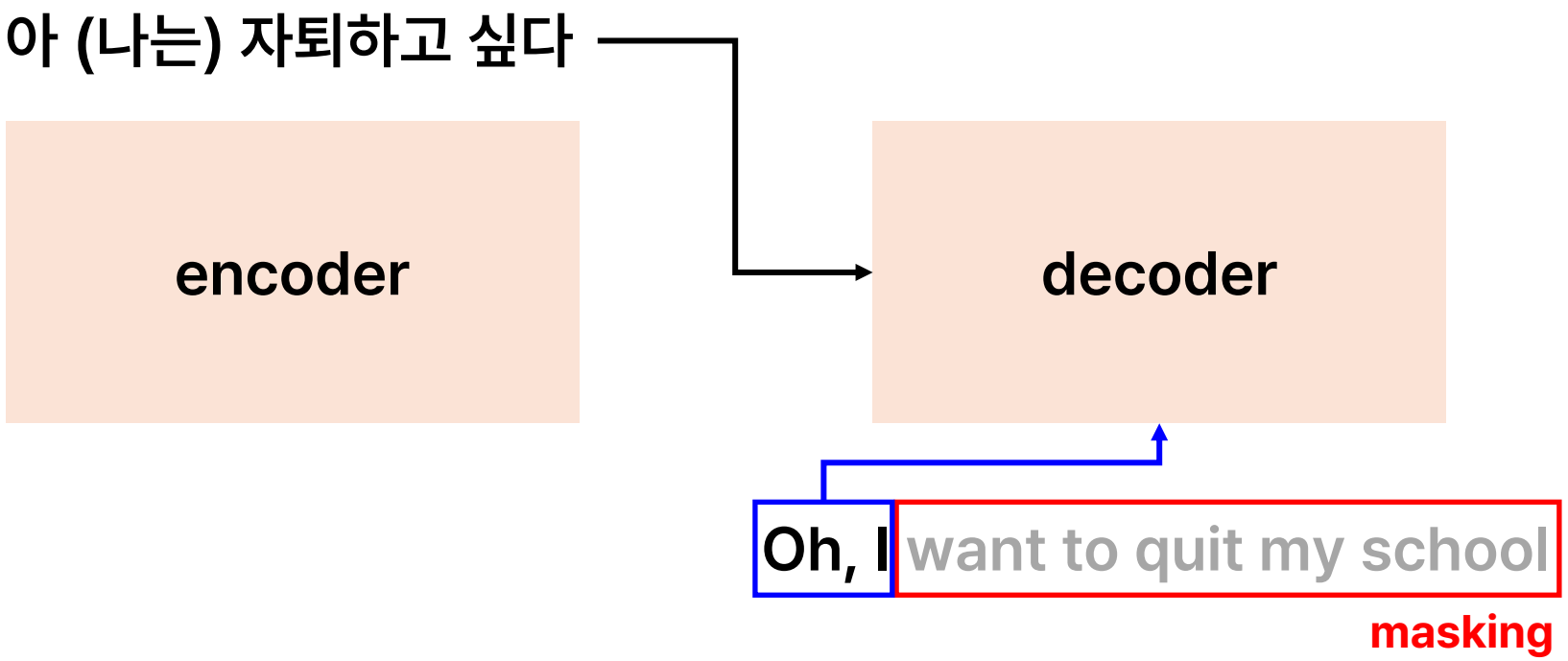
want to를 출력하고 싶은데
school을 이미 학습한 상태라면?
-> 학습에 혼동

3. Masked Multi-head attention

아 (나는) 자퇴하고 싶다 ⟶ Oh, I want to quit my school

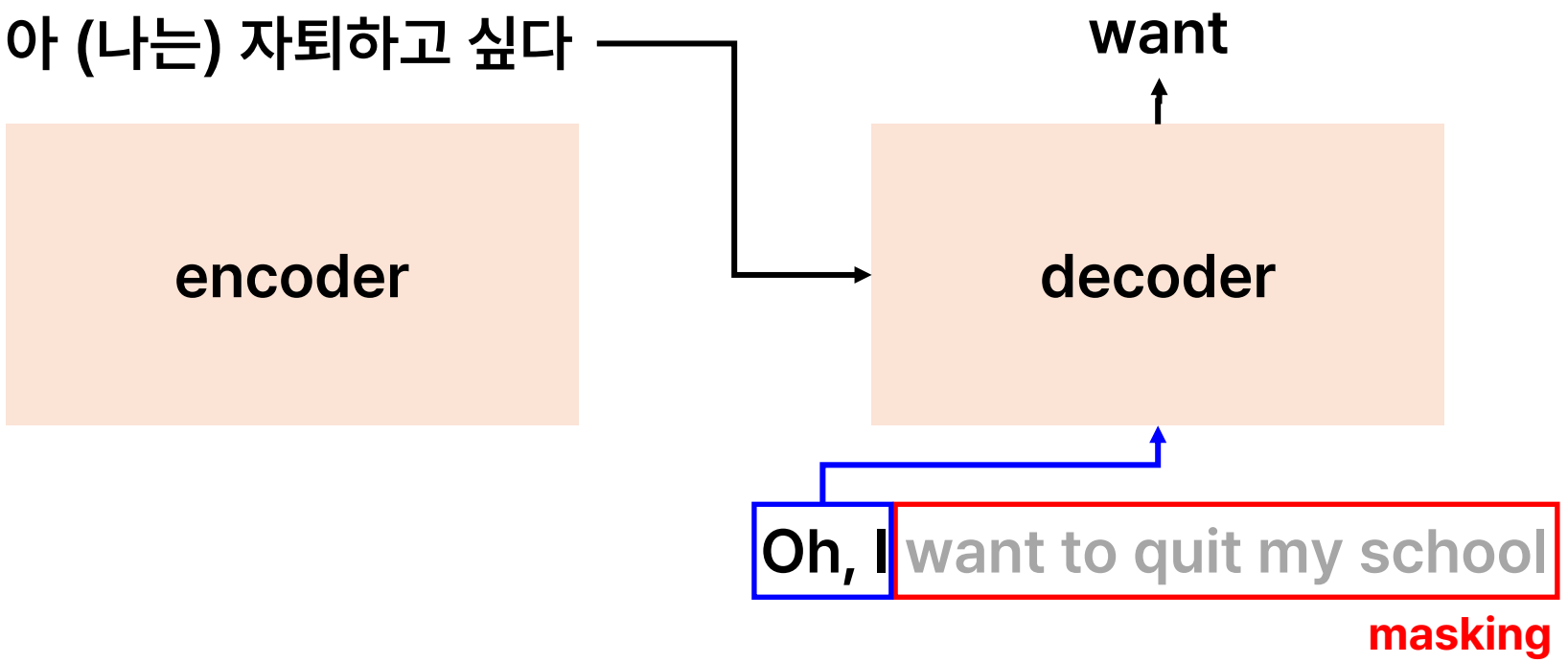
want to를 출력하고 싶은데
school을 이미 학습한 상태라면?
-> 학습에 혼동
-> 그럼 뒤에 단어는 지우고 학습해~

3. Masked Multi-head attention



3. Masked Multi-head attention

-> 3번째 단어를 예측하기 위해 2번째 단어까지만 사용
나머지 단어들 masking



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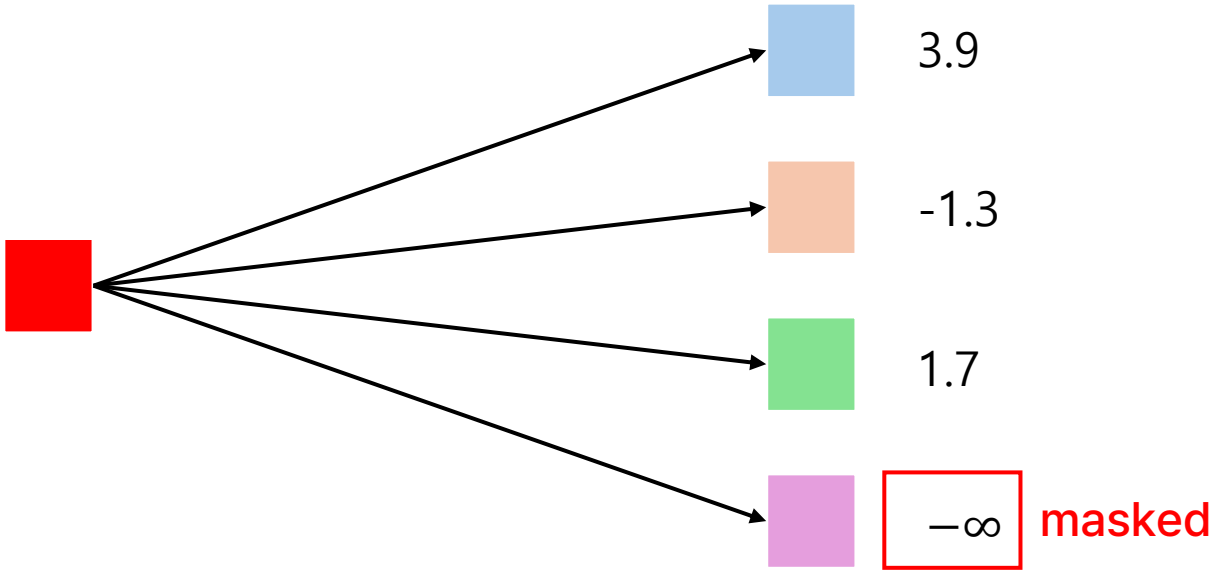
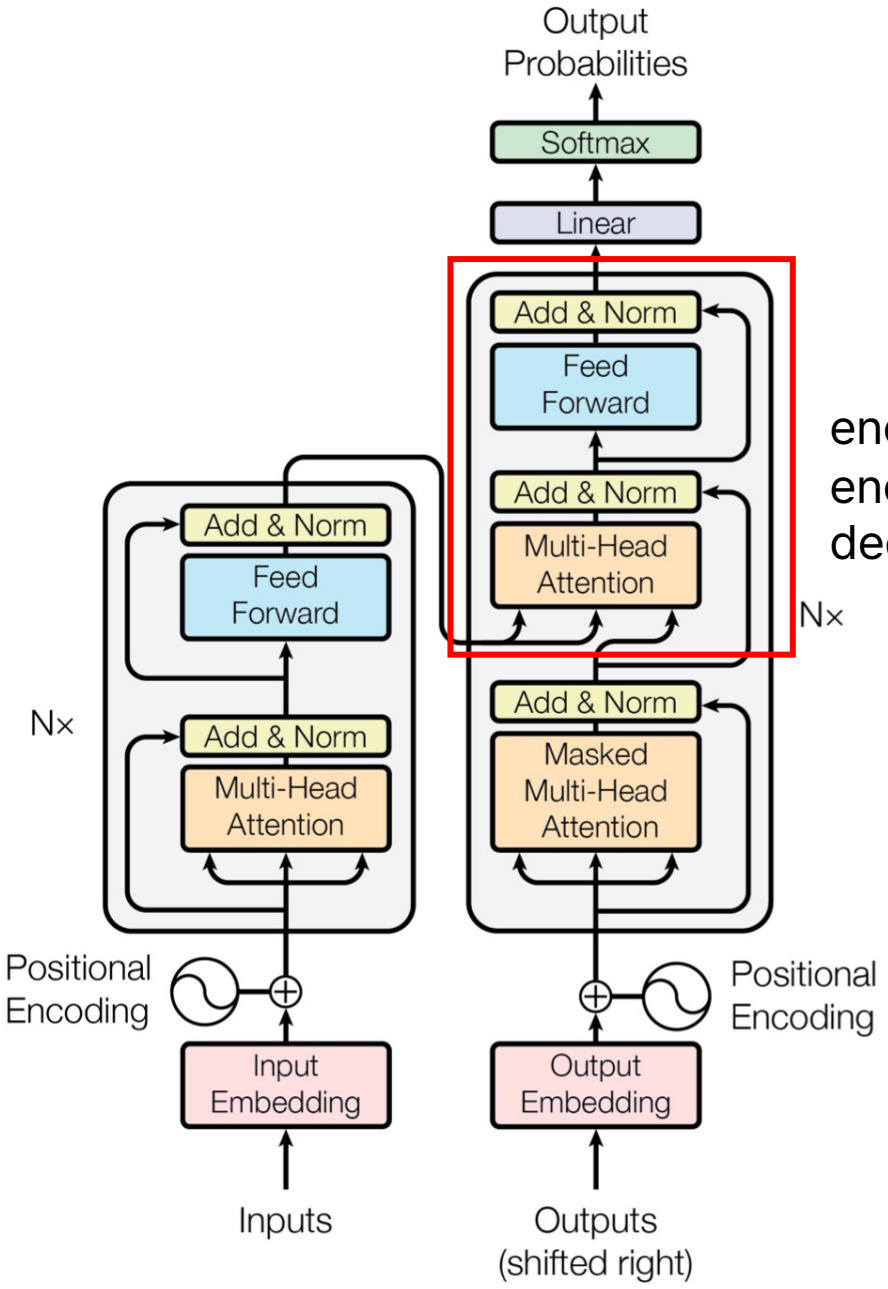
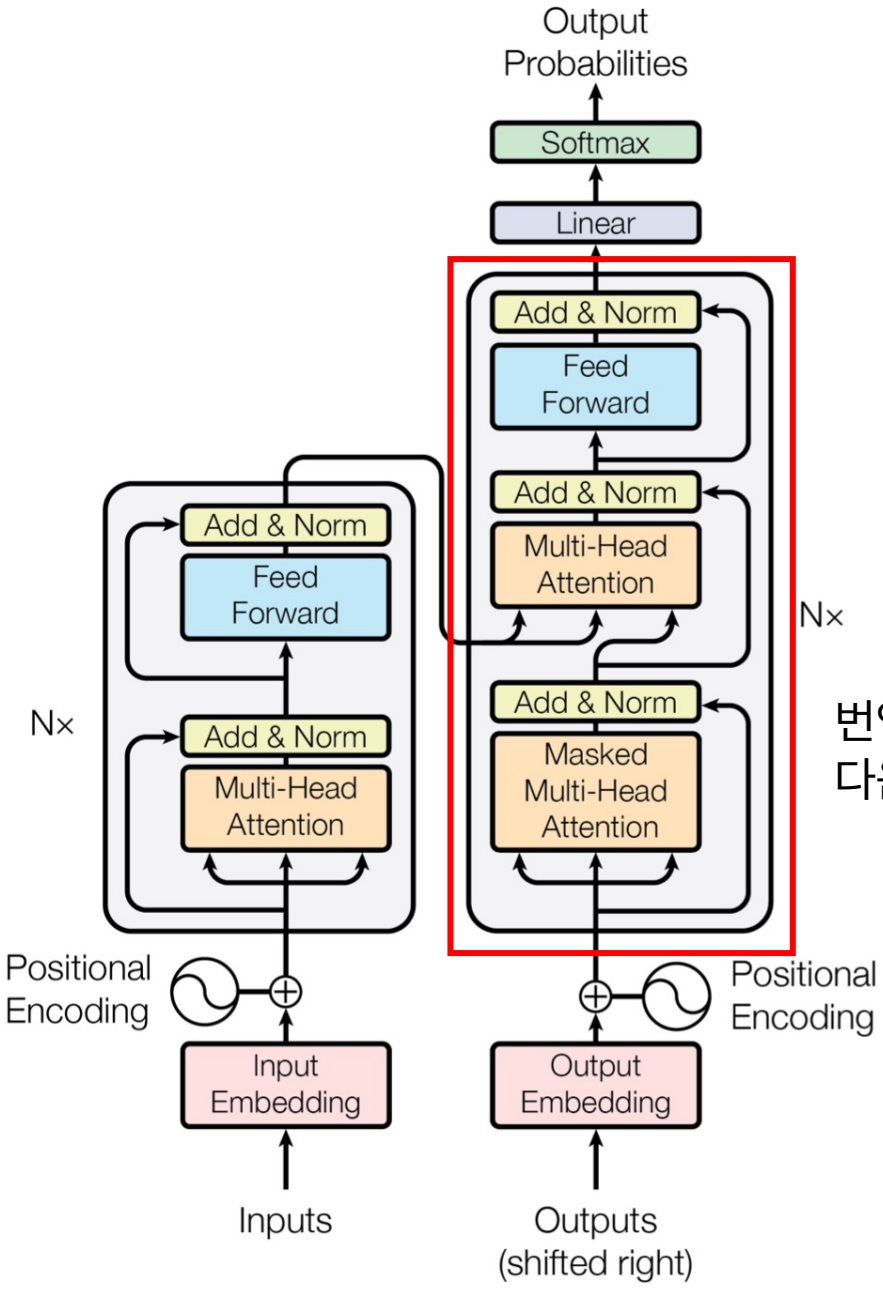




encoder 구조와 동일
encoder output을
decoder의 input(key, value)으로 사용

Figure 1: The Transformer - model architecture.



번역할 문장과 번역된 문장의 정보를 바탕으로 다음의 올 단어를 예측

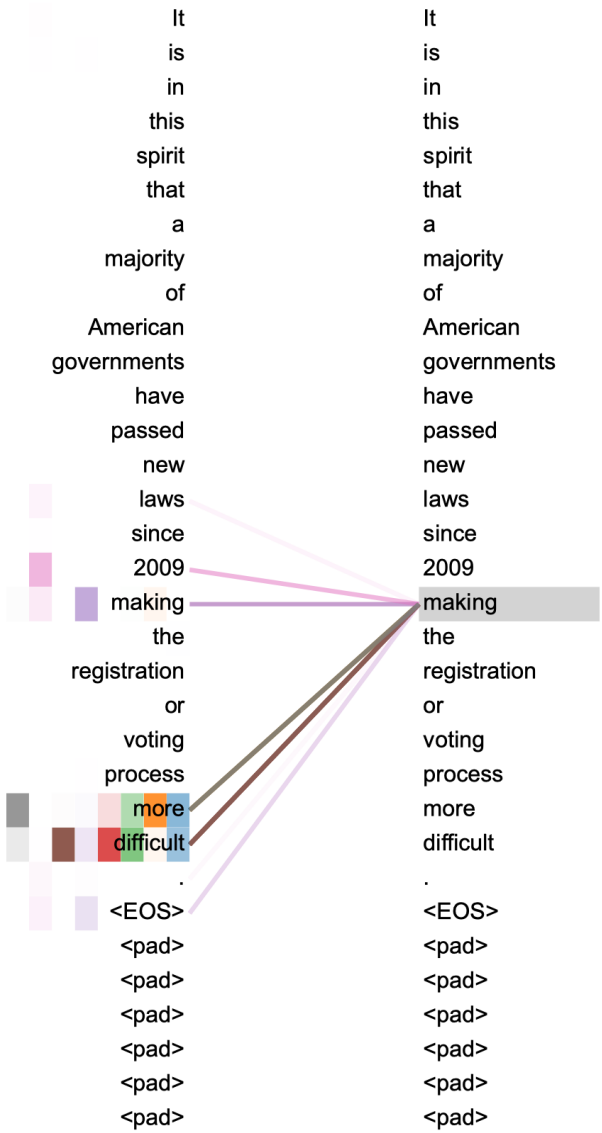
Figure 1: The Transformer - model architecture.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

1. Data : standard WMT 2014 English – German dataset, English– French dataset
   - 4.5million, 3.6million개의 문장 pairs
   - 37000, 25000개의 tokens
2. Hardware and Schedule
   - 8대의 NVIDIA P100 GPU 사용
   - base model : 0.4s/step -> 100,000step : 12h 소요
   - big model : 1.0s/step -> 300,000step : 1d 소요
3. Optimizer : Adam
   - $lrate = d_{\text{model}}^{-0.5} \cdot \min(step\_num^{-0.5}, step\_num \cdot warmup\_steps^{-1.5})$
   - $\beta_1 = 0.9, \beta_2 = 0.98, \varepsilon = 10^{-9}$
4. Regularization
   - Dropout : p=0.1
   - Label smoothing(one-hot encoding을 약간 부드럽게 하여 모델이 너무 확산되지 않도록 함)
     - $y_i' = (1-\epsilon)y_i + \frac{\epsilon}{K}$
     - $\varepsilon = 0.1$

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

1. BLEU(번역된 문장의 품질 평가 점수)제일 높음
2. training cost 제일 작음(big model도 작은 축에 속함)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is
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spirit
that
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majority
of
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passed
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making
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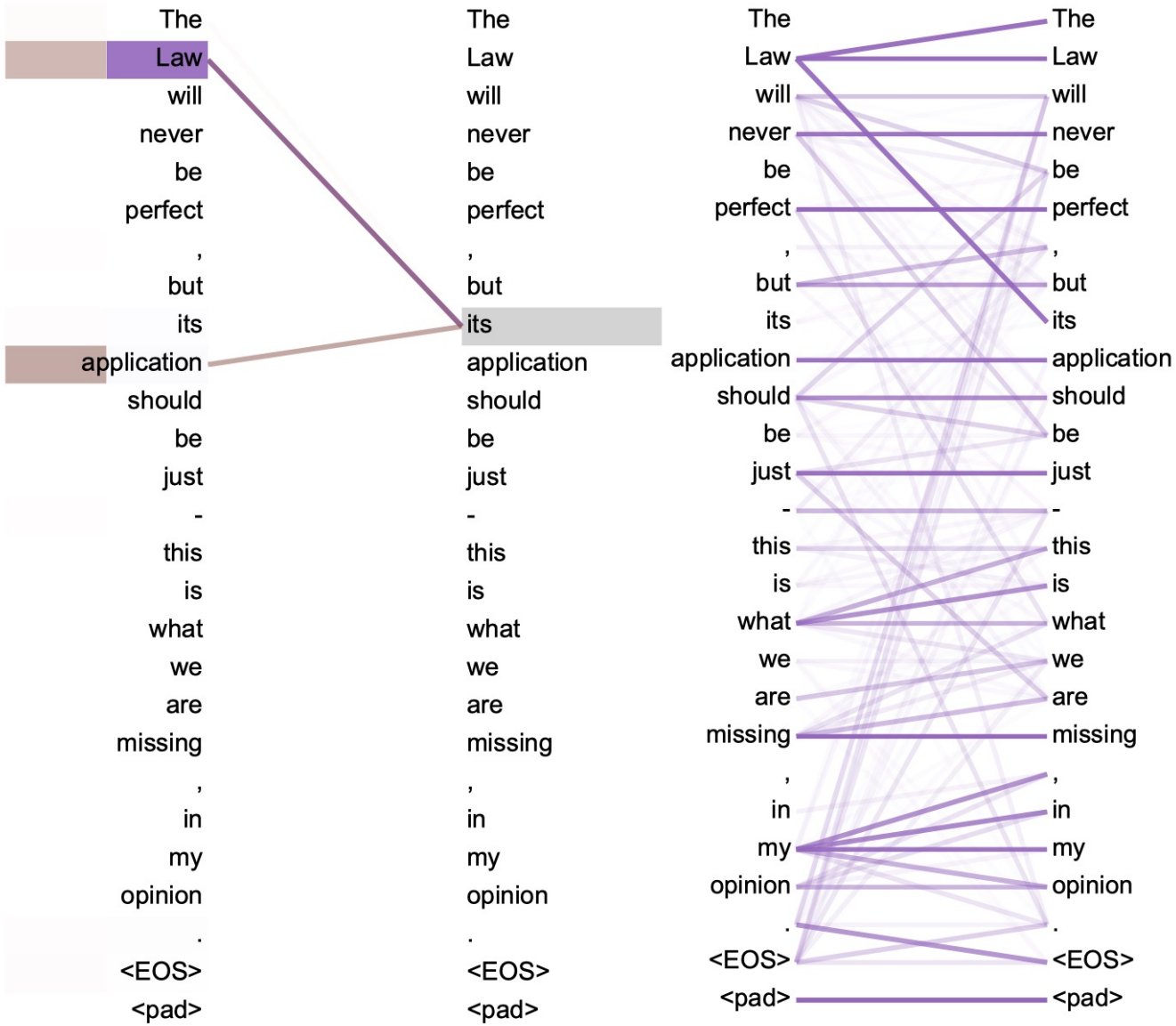
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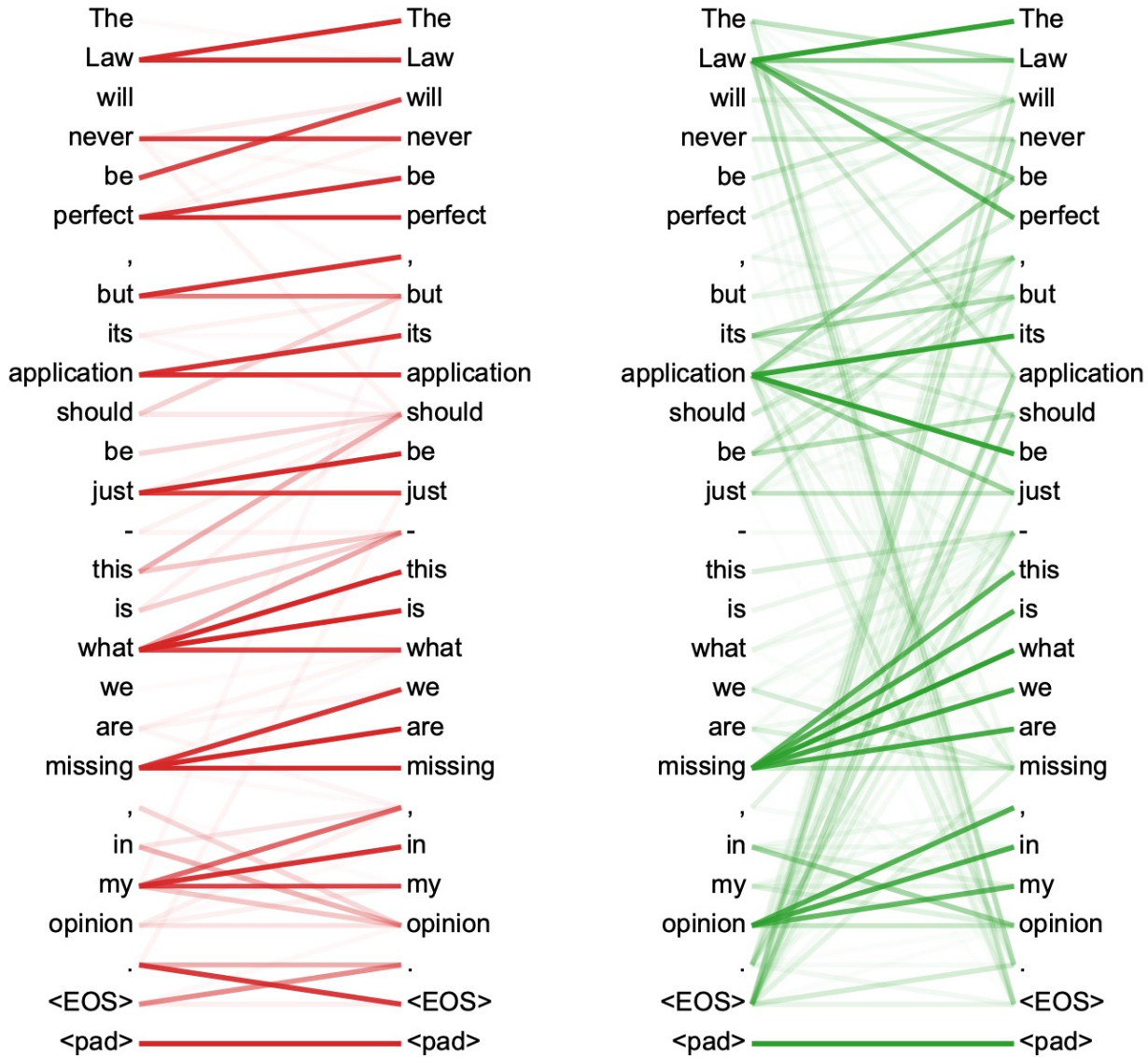
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