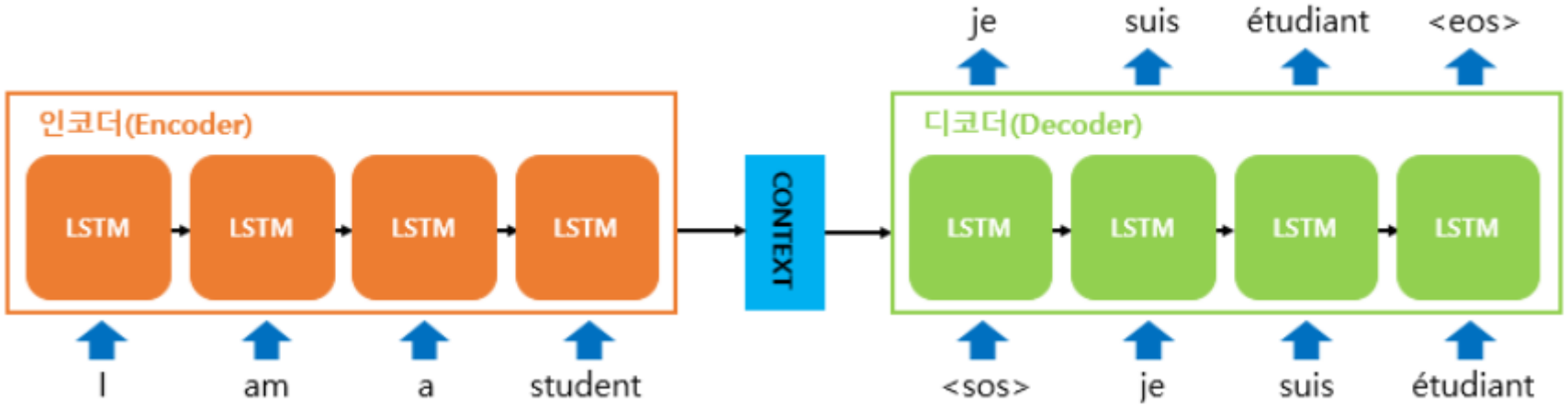
Transformer

19/11/10

목차

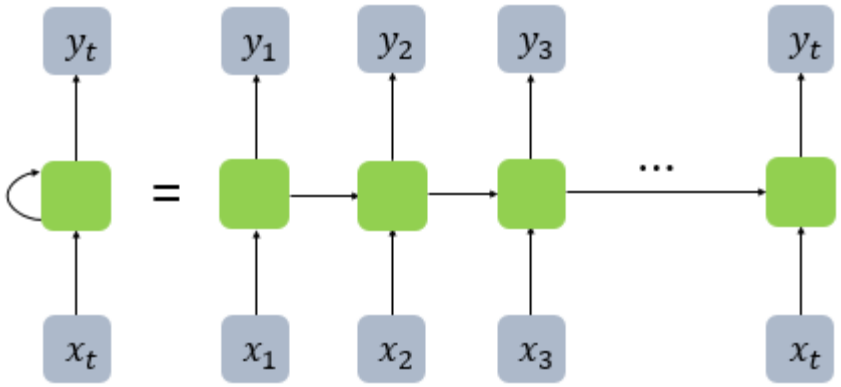
Seq2Seq

- 입력된 시퀀스로부터 다른 도메인의 시퀀스를 출력하는 모델
- 챗봇, 기계 번역에 사용됨



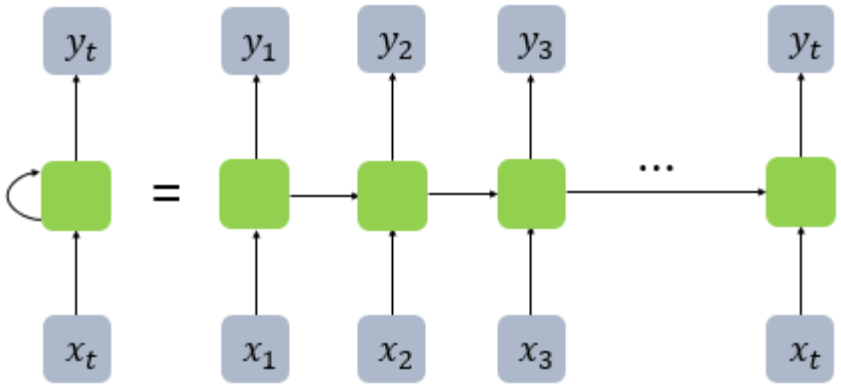
기존의 Recurrent 모델의 문제점

- Long-term dependency problem
  - 분명 순차적으로 Sequence를 처리하지만, Time Step이 늘어날 수록 성능이 떨어진다.
- Parallelization
  - T번째 hidden state를 얻기 위해서 t-1번째 hidden state가 필요하다. -> 순서대로 계산되어야 한다. -> 병렬처리 불가능 -> 계산 느림



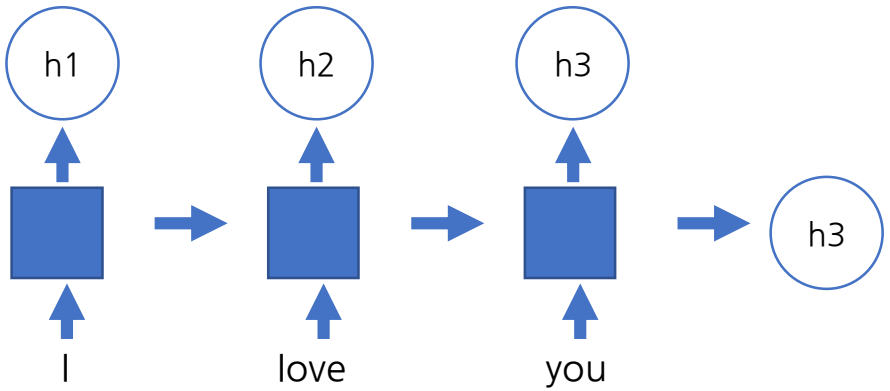
So we suggest Transformer

- ~~Long-term dependency problem~~
  - ~~분명 순차적으로 Sequence를 처리하지만, Time Step이 늘어날 수록 성능이 떨어진다~~
- ~~Parallelization~~
  - ~~T번째 hidden state를 얻기 위해서 t-1번째 hidden state가 필요하다. -> 순서대로 계산되어야 한다. -> 병렬처리 불가능 -> 계산 느림~~
- Attention
  - Recurrece를 사용하지 않고 input과 outpu의 dependency 포착
  - 행렬 계산으로 한 번에 병렬처리 가능

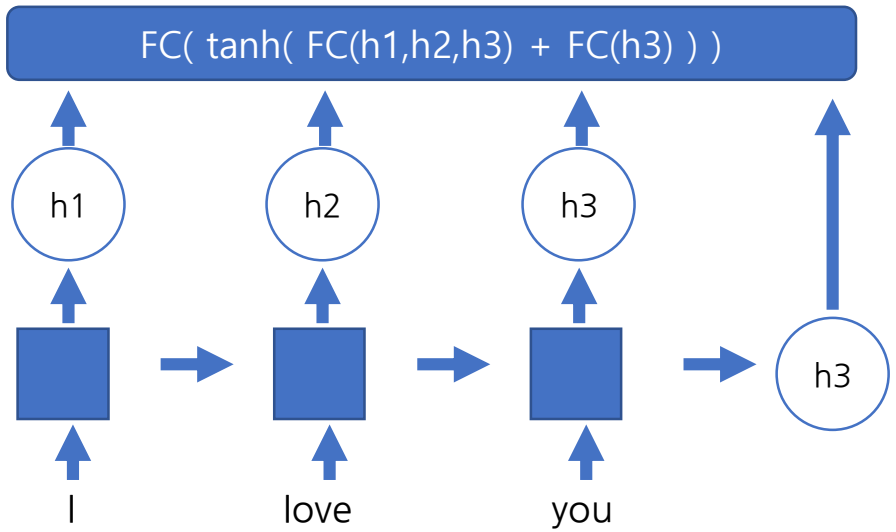


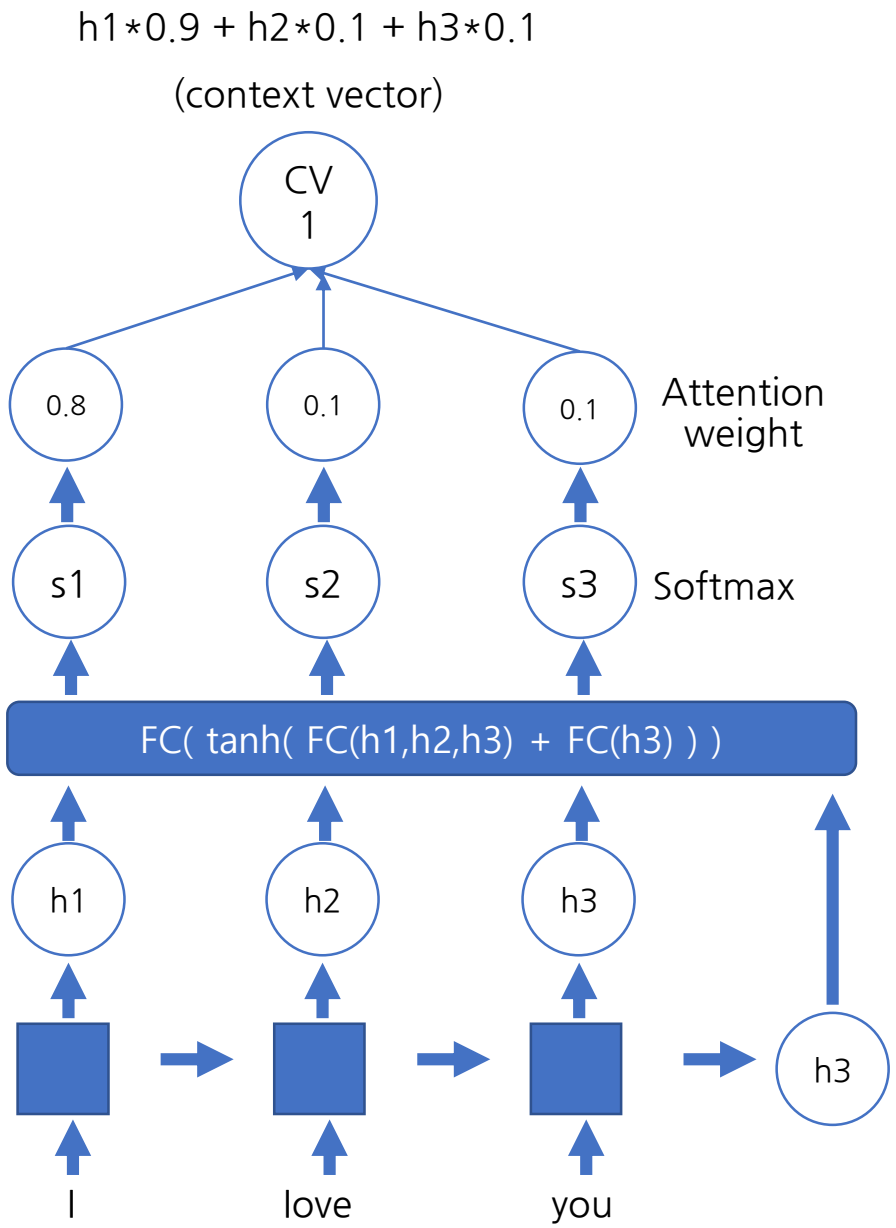
일단 Attention이 뭐죠?

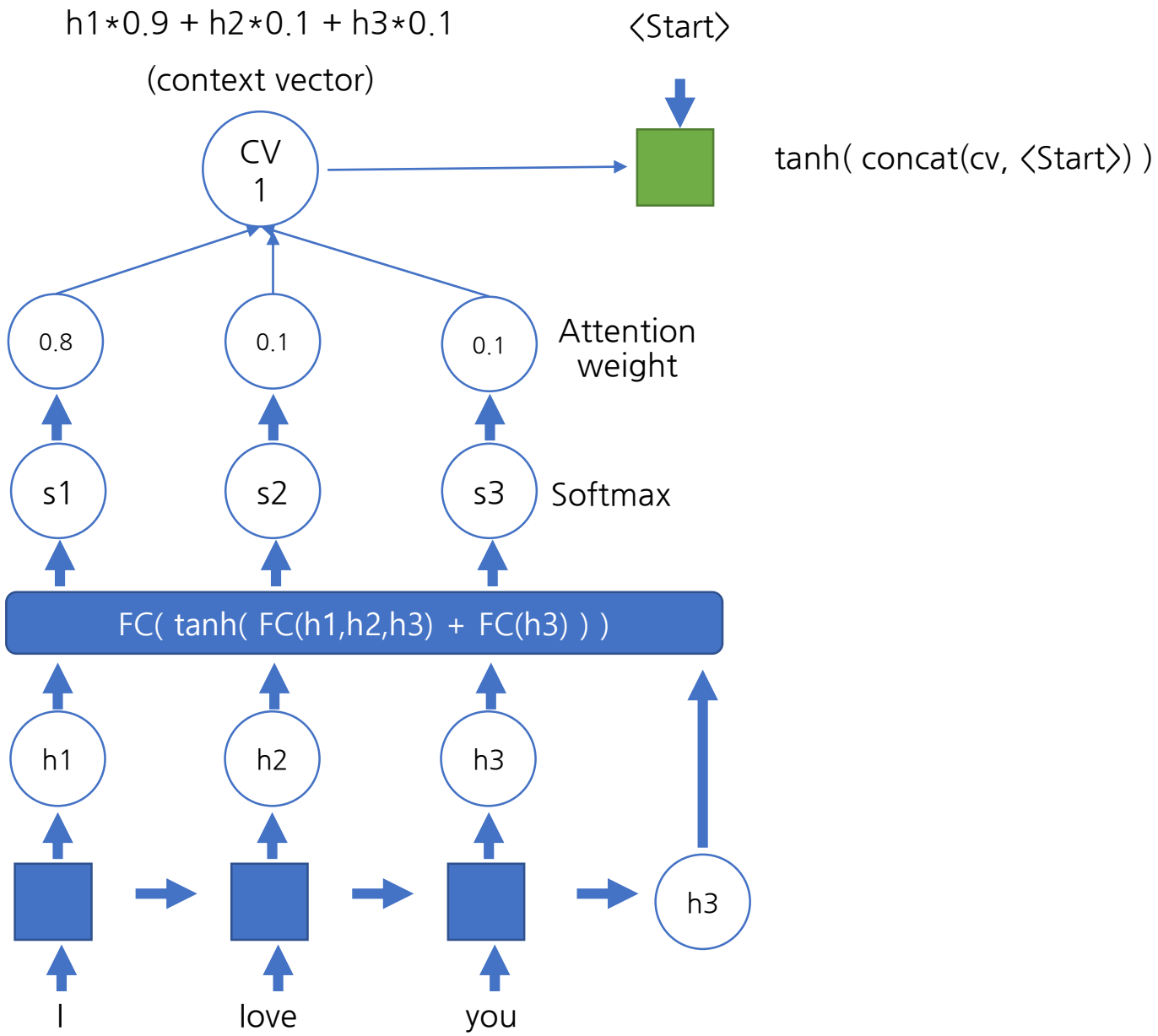
- Seq2Seq에서의 Attention
  - 디코더에서 출력 단어를 예측하는 매 time step마다, 인코더의 전체 입력을 다시 참고
  - 이 때, 특정 시점에서 예측해야할 단어와 연관이 있는 단어에 좀 더 “집중”하게 됨

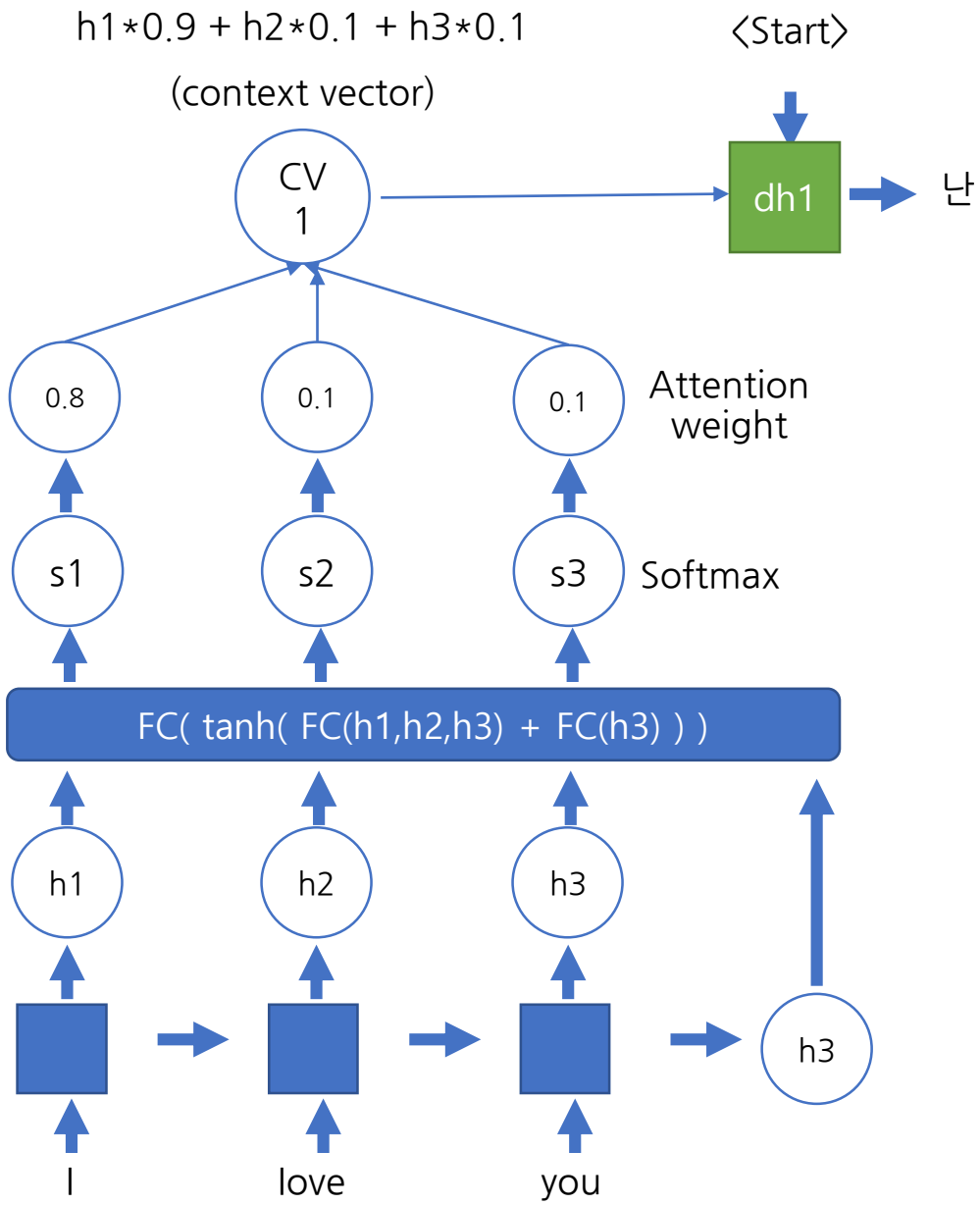


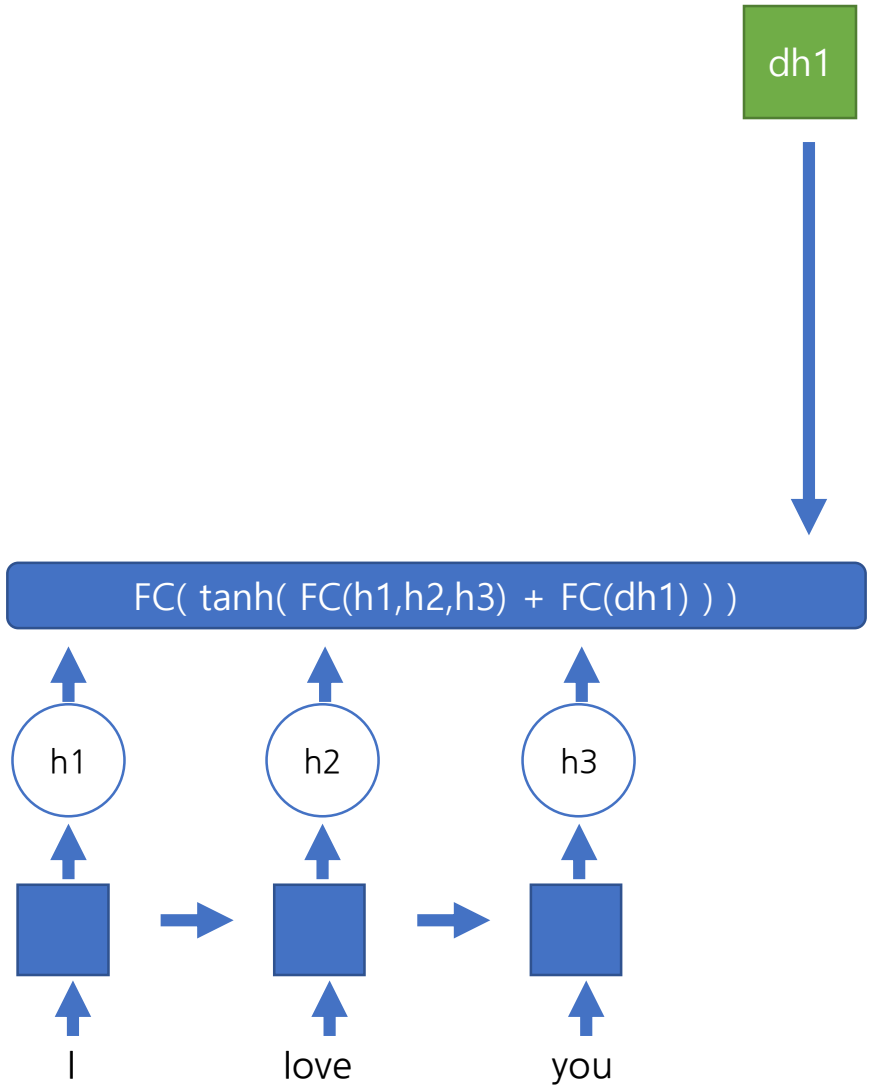
I love you -> 난 널 사랑해

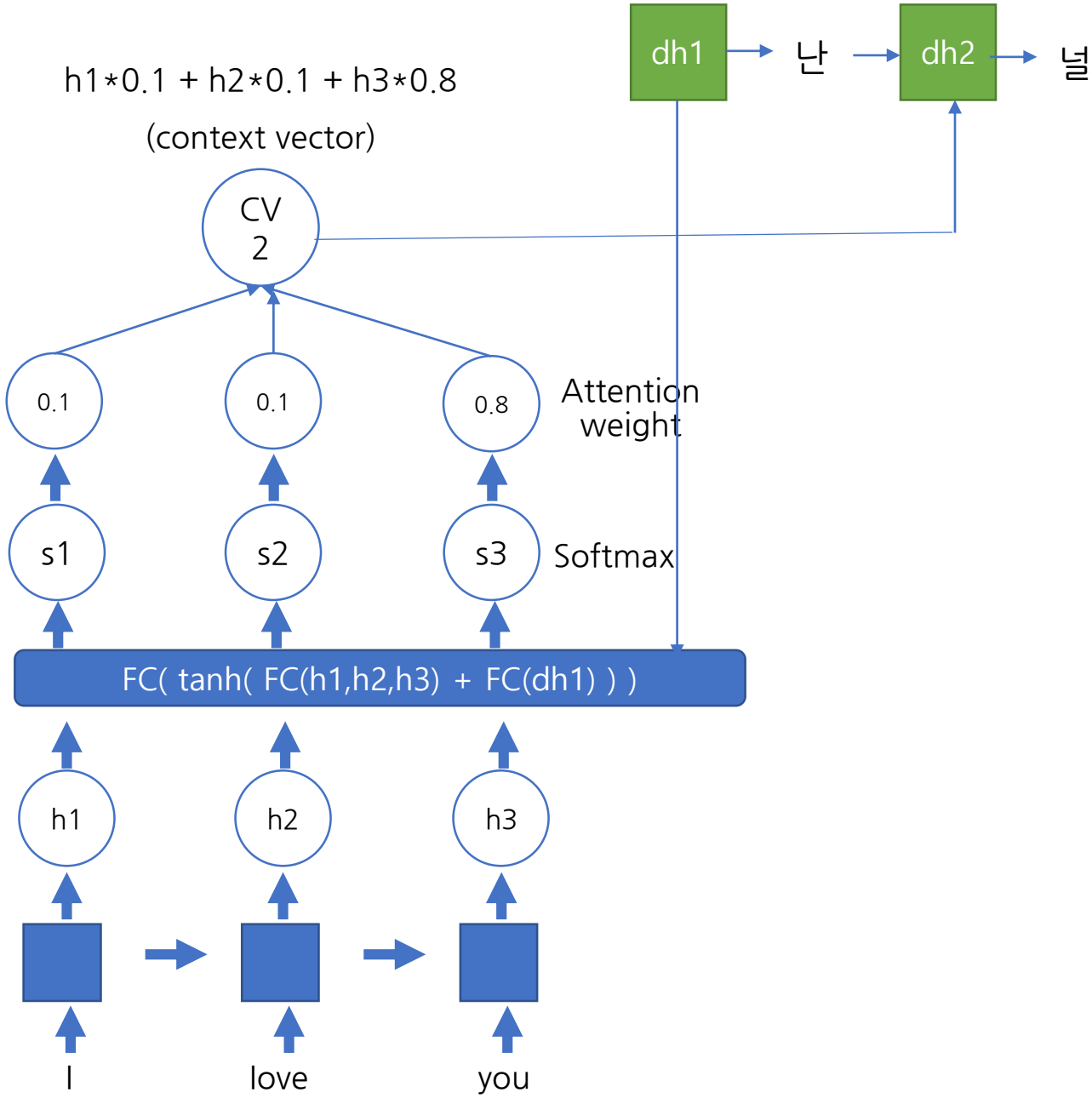

FC(tanh(FC(h1,h2,h3) + FC(h3)))
h1
h2
h3
h3
I
love
you

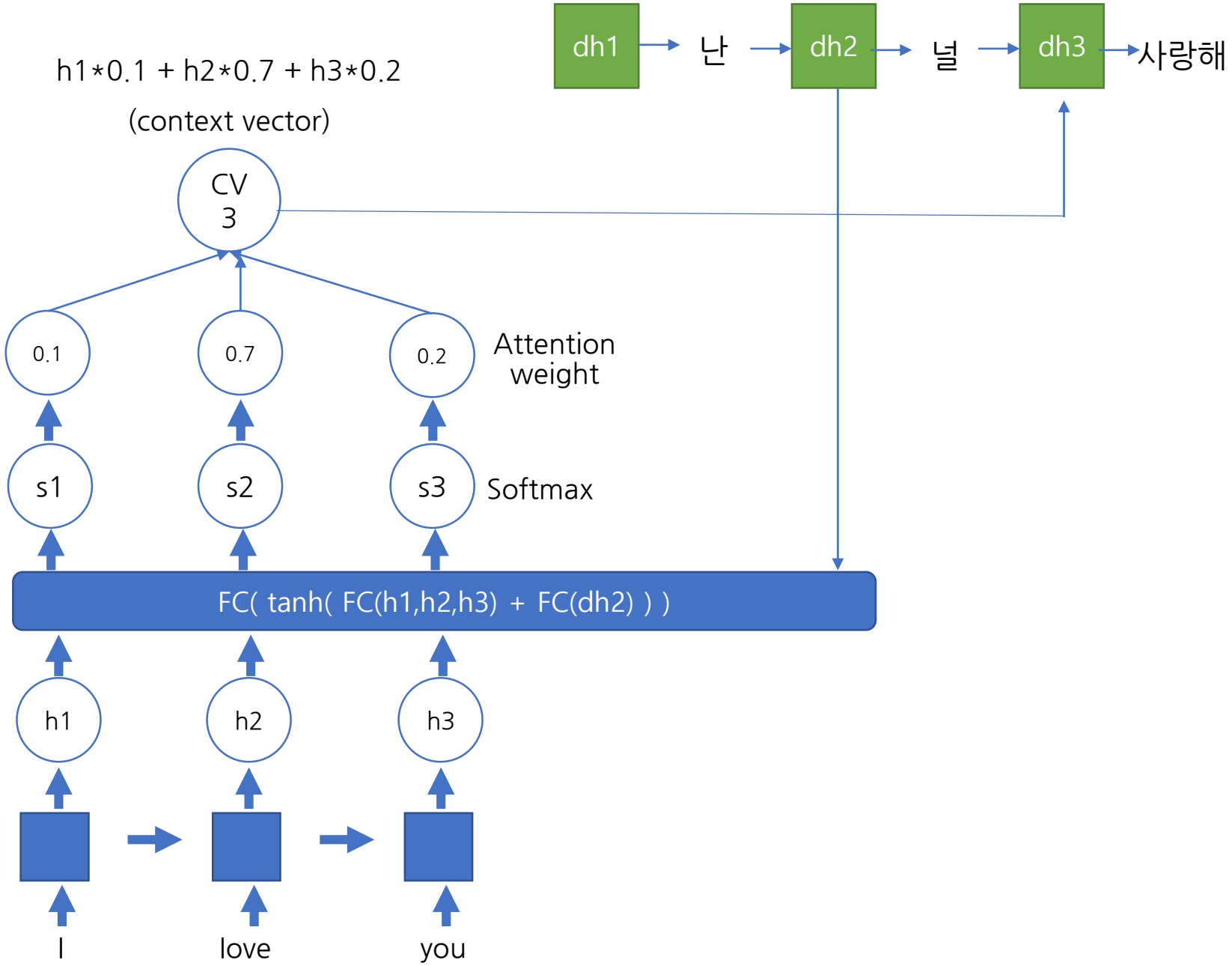

h1*0.9 + h2*0.1 + h3*0.1
(context vector)
CV
1
0.8
0.1
0.1
Attention
weight
s1
s2
s3
Softmax
FC(tanh(FC(h1,h2,h3) + FC(h3)))
h1
h2
h3
h3
I
love
you

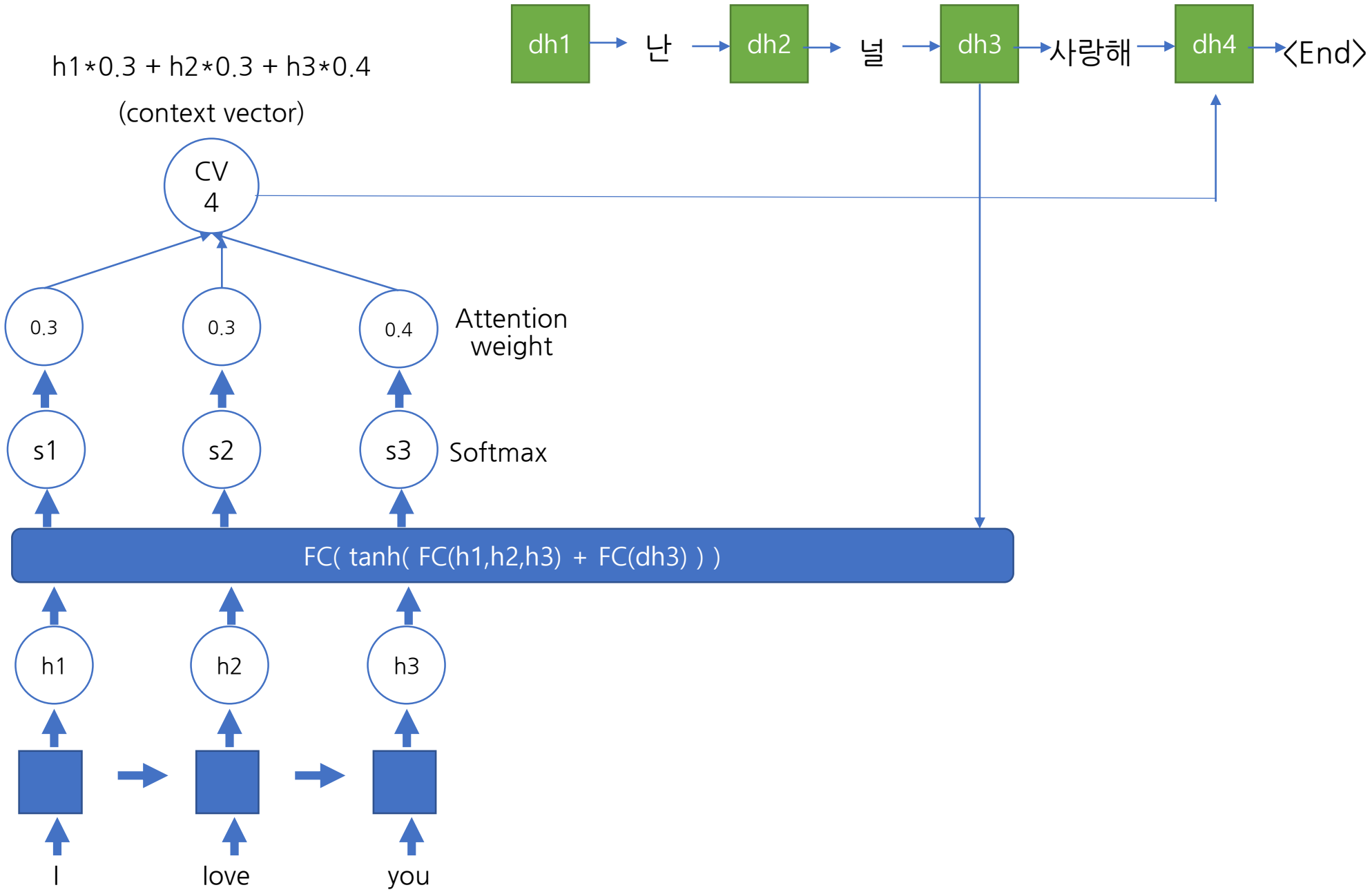

h1*0.9 + h2*0.1 + h3*0.1
(context vector)
<Start>
CV
1
tanh(concat(cv, <Start>))
0.8
0.1
0.1
Attention
weight
s1
s2
s3
Softmax
FC(tanh(FC(h1,h2,h3) + FC(h3)))
h1
h2
h3
h3
I
love
you


h1*0.9 + h2*0.1 + h3*0.1
(context vector)
<Start>
CV
1
dh1
난
0.8
0.1
0.1
Attention
weight
s1
s2
s3
Softmax
FC(tanh(FC(h1,h2,h3) + FC(h3)))
h1
h2
h3
h3
I
love
you


dh1
FC(tanh(FC(h1,h2,h3) + FC(dh1)))
h1
h2
h3
I
love
you


h1*0.1 + h2*0.1 + h3*0.8
(context vector)
CV
2
dh1
난
dh2
너
0.1
0.1
0.8
Attention
weight
s1
s2
s3
Softmax
FC(tanh(FC(h1,h2,h3) + FC(dh1)))
h1
h2
h3
I
love
you


h1*0.1 + h2*0.7 + h3*0.2
(context vector)
dh1
난
dh2
널
dh3
사랑해
CV
3
0.1
0.7
0.2
Attention
weight
s1
s2
s3
Softmax
FC(tanh(FC(h1,h2,h3) + FC(dh2)))
h1
h2
h3
I
love
you


h1*0.3 + h2*0.3 + h3*0.4
(context vector)
dh1
난
dh2
널
dh3
사랑해
dh4
〈End〉
CV
4
0.3
0.3
0.4
Attention
weight
s1
s2
s3
Softmax
FC(tanh(FC(h1,h2,h3) + FC(dh3)))
h1
h2
h3
I
love
you

서론이 길었습니다. 이제 Transformer에요.

- RNN기반 Seq2Seq는 문제점이 꽤 많았다.
- 아예 RNN을 빼버리고 Attention으로만 인코더와 디코더를 만들어볼까?

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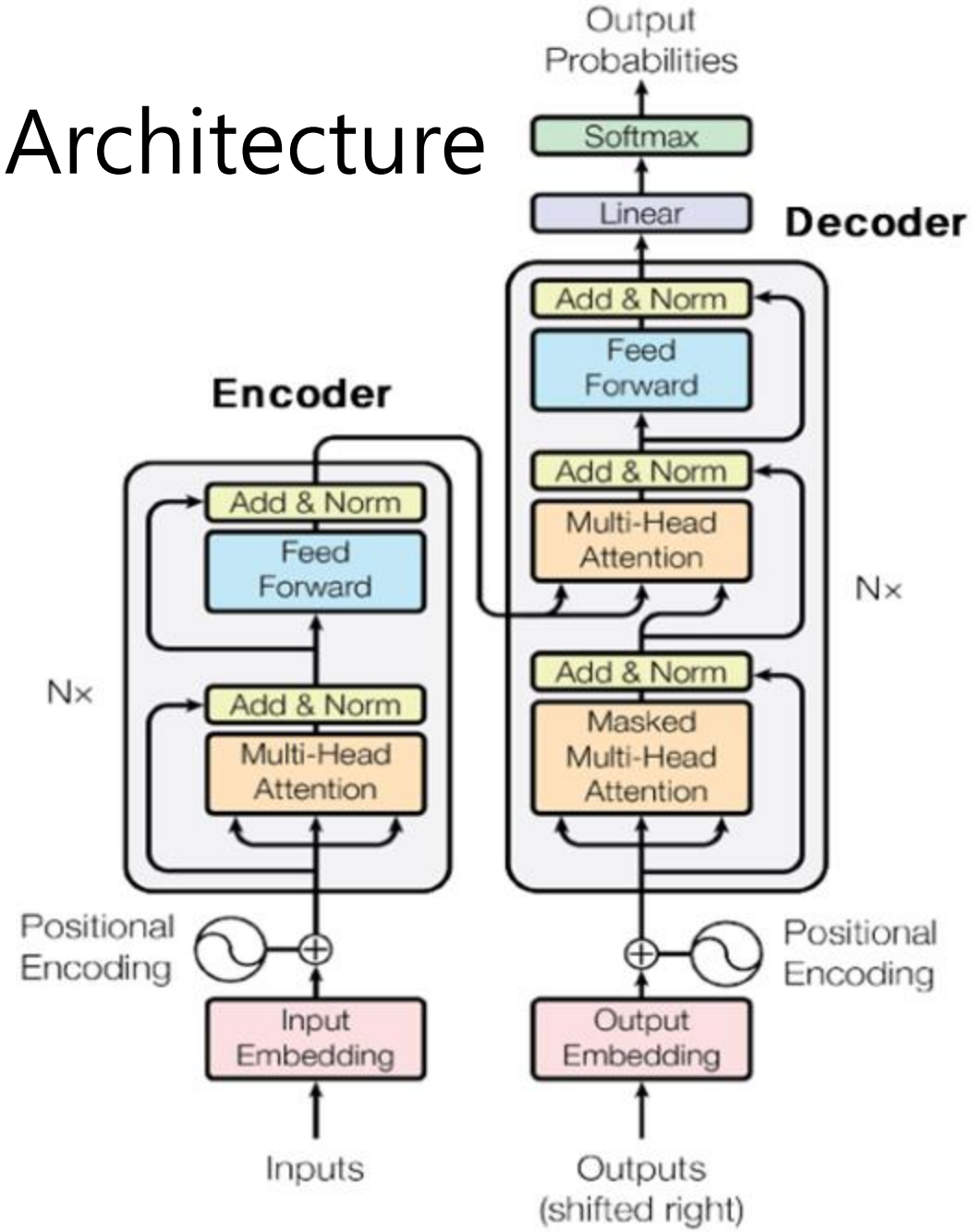
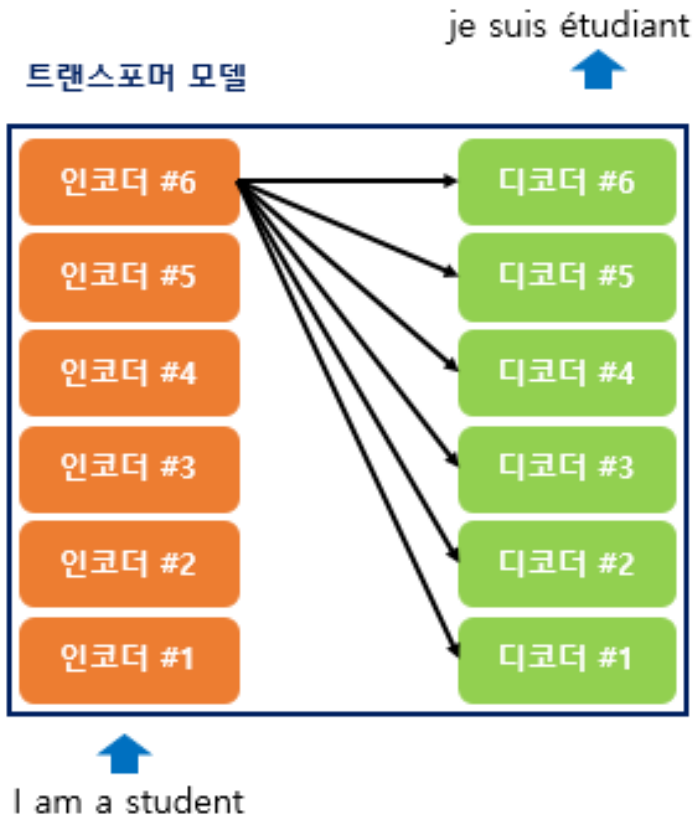
Transformer Architecture

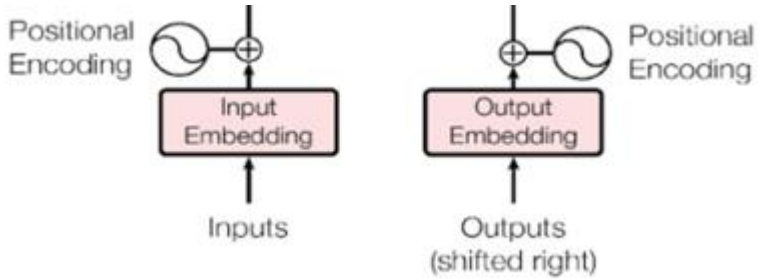


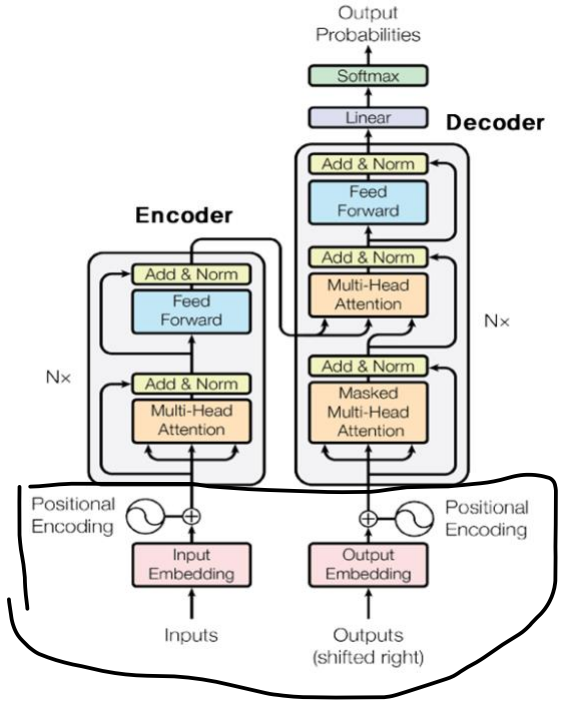
Transformer Architecture



1. Representation

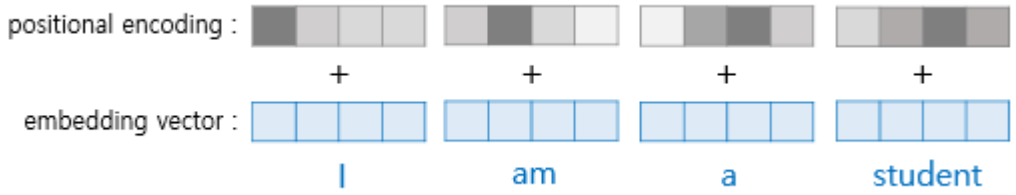
- Transformer는 RNN과 달리 단어의 위치 정보를 가질 수 없다.
- 위치 정보를 알려주기 위하여 Positional Encoding을 하자.

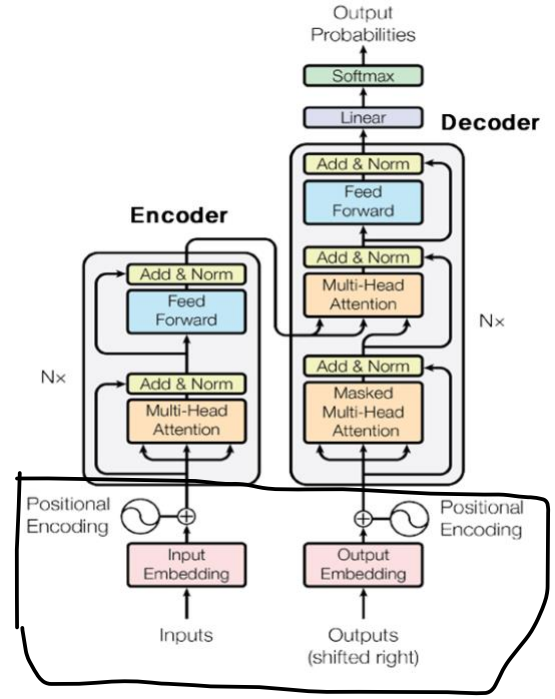




1. Representation

- How? Pos encoding값과 Embedding Vector를 더하면 된다.
  - 같은 단어라고 하더라도 문장 내 위치에 따라서 임베딩 벡터값이 달라진다.

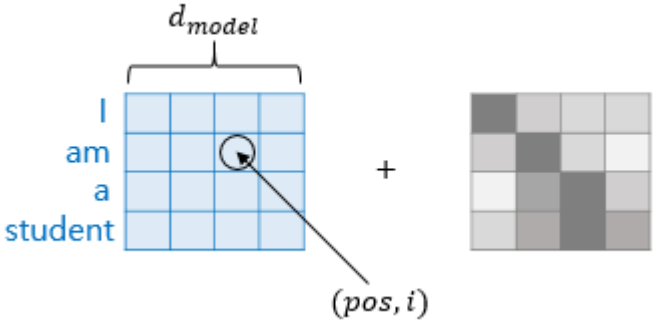




- Transformer 논문에서는 위치정보 값을 만들기 위해 두 개의 함수 사용

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

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



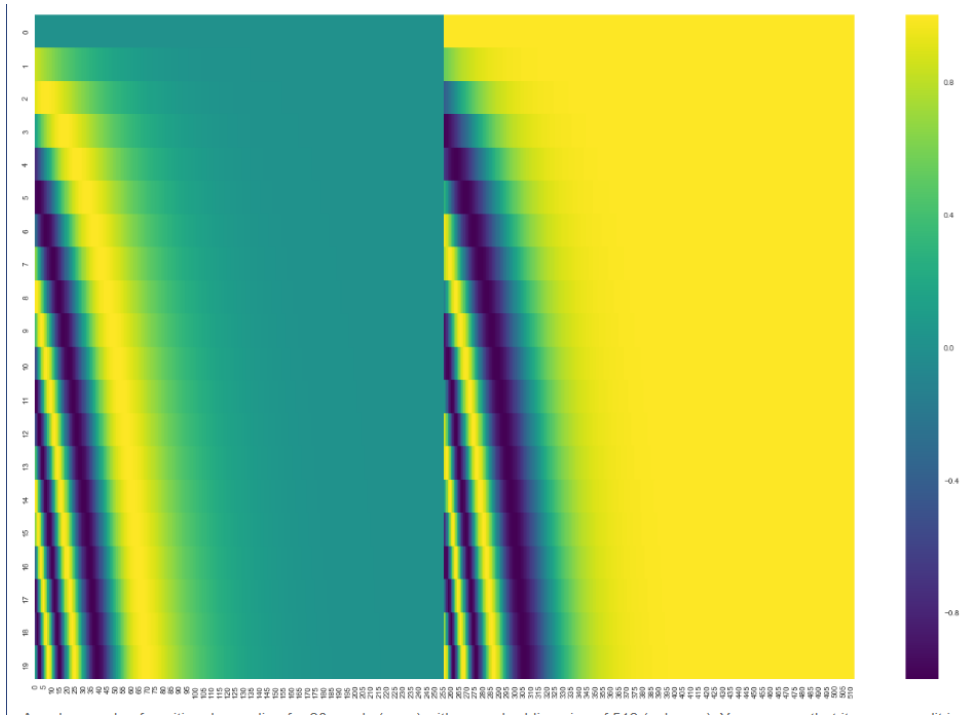
1. Representation

- 왜 Sine, Cosine 함수를 쓰지?

It, however, gives the advantage of being able to scale to unseen lengths of sequences

(e.g. if our trained model is asked to translate a sentence longer than any of those in our training set).

- The Illustrated Transformer (Jay Alammar)

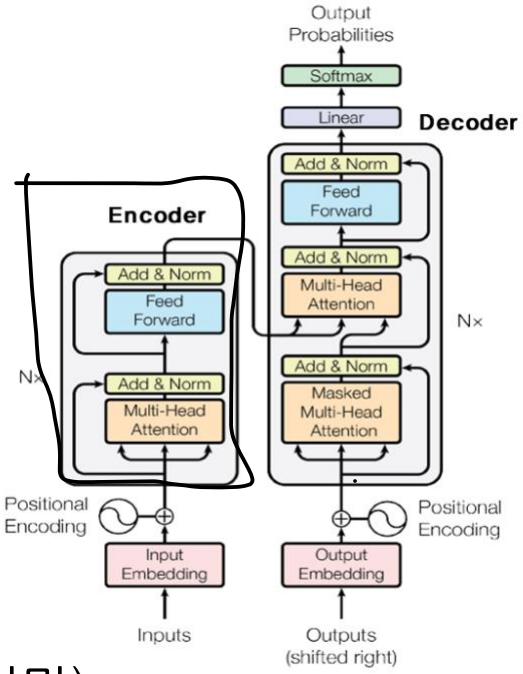


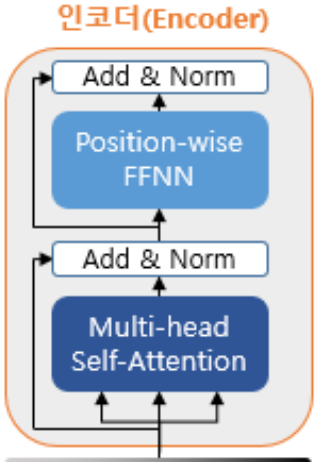
2. Encoder

- Encoder는 2개의 Sublayer로 구성

1. Multi-head Self-Attention

2. Position-wise Feed Forward Neural Network (강 Fully-connected 신경망)

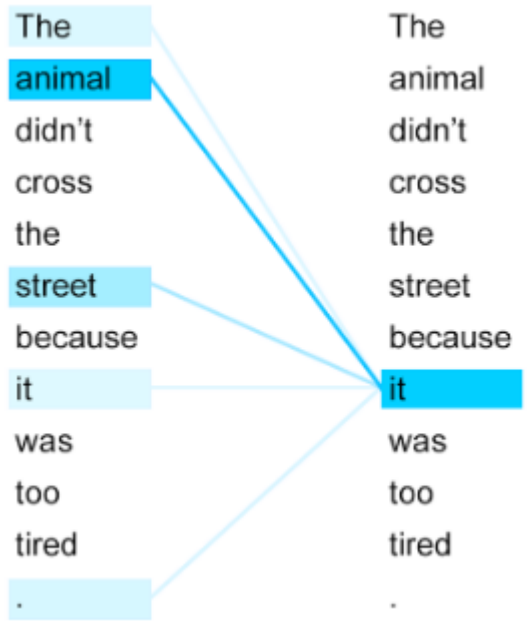


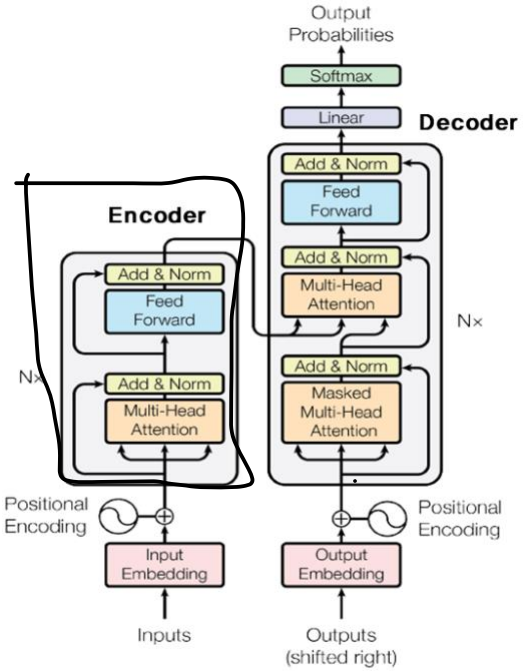


2.1 Self-Attention

- 기존 Seq2Seq의 Attention은 다른 두 문장이었다면 이번엔 자기 자신에 Attention을 한다.

- Why?
  - It이 무엇을 가르킬까?
  - 기존 Seq2Seq 구조로는 알 수 없는 정보이다.



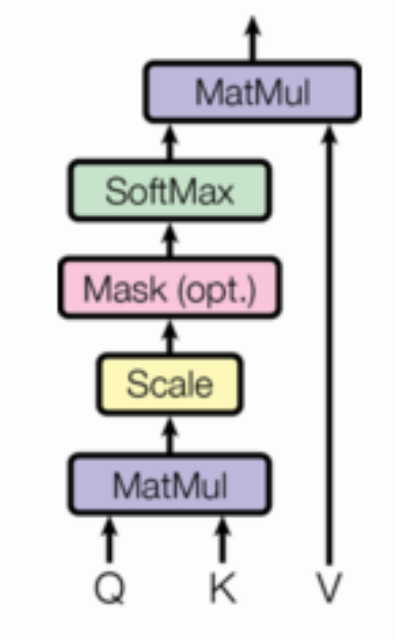


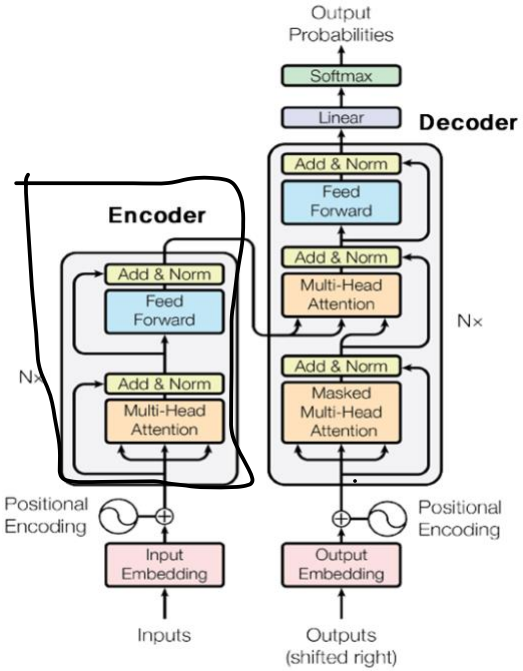
2.1 Self-Attention

- Q, K, V 벡터
  - Attention에는 Query, Key, Value가 있다.
  - 주어진 쿼리에 대해서 모든 키와의 유사도를 각각 구한다.
  - 이 유사도를 가중치로 하여 키와 맵핑되어있는 각각의 값에 반영한다. 그리고 유사도가 반영된 값을 모두 가중합한다.

```
Q = Query : t-1 시점의 디코더 셀에서의 은닉 상태
K = Keys : 모든 시점의 인코더 셀의 은닉 상태들
V = Values : 모든 시점의 인코더 셀의 은닉 상태들
```

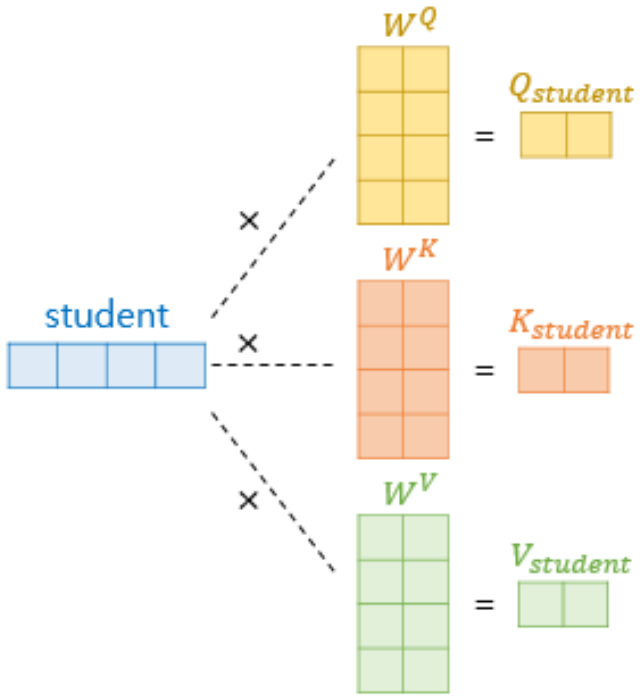
- 이해가 안된다면 일단 따라와주세요





2.1 Self-Attention

- Wq, Wk, Wv는 weight 파라미터로, 학습될 예정
- 각 Q,K,V는 독립된 Matrix, shape은 $d_{model} \times (d_{model}/num\_heads)$



- 하이퍼파라미터

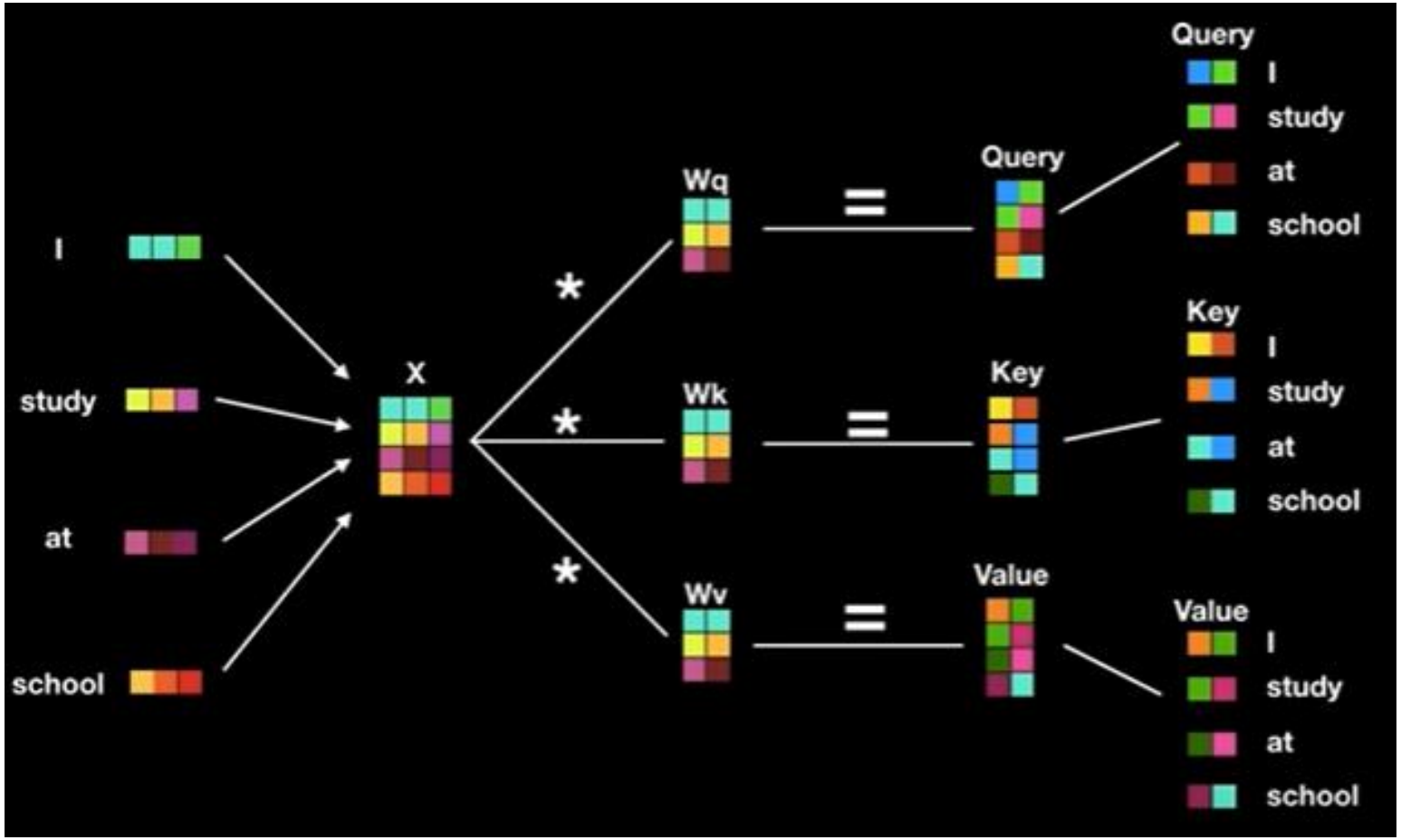
d_{model} : 인코더와 디코더 입력과 출력 크기

Num_layers : 레이어의 층 수

Num_heads : 어텐션을 병렬로 하기 위한 어텐션 개수

d_{ff} : FC-layer 은닉층 크기

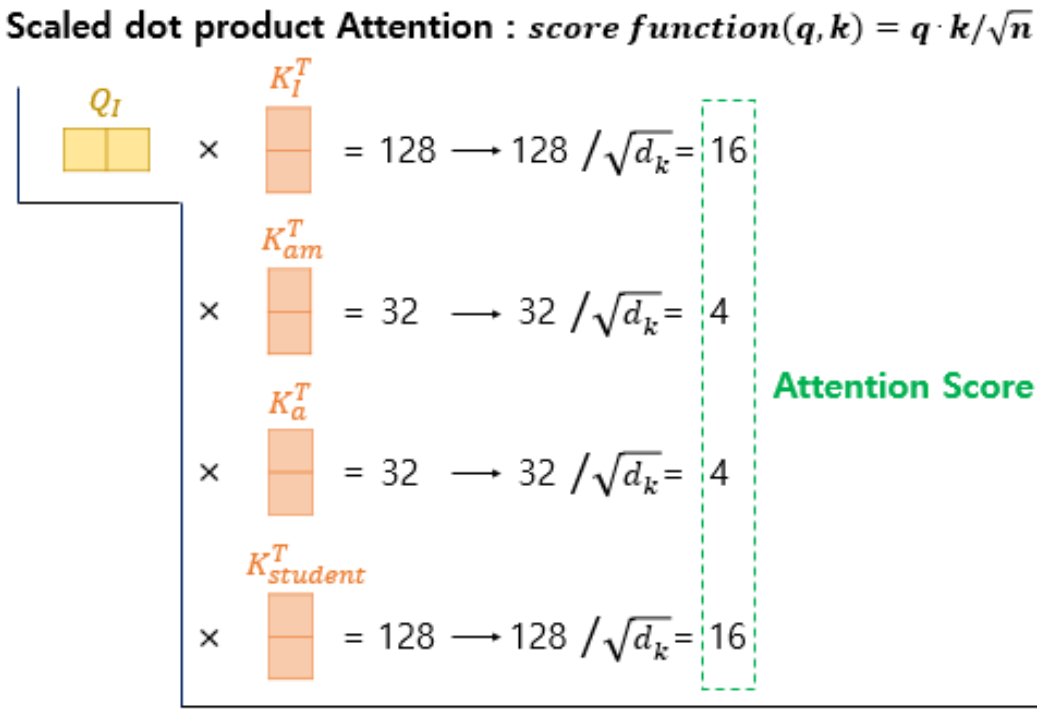
2.1 Self-Attention



- https://www.youtube.com/watch?v=mxGCEWOxfe8

2.1 Self-Attention

- Scaled dot product Attention
  - 트랜스포머에서는 두 벡터의 내적값을 스케일링하는 값으로 d_k에 루트를 씌운 $\sqrt{d_k}$ 사용함.



2.1 Self-Attention

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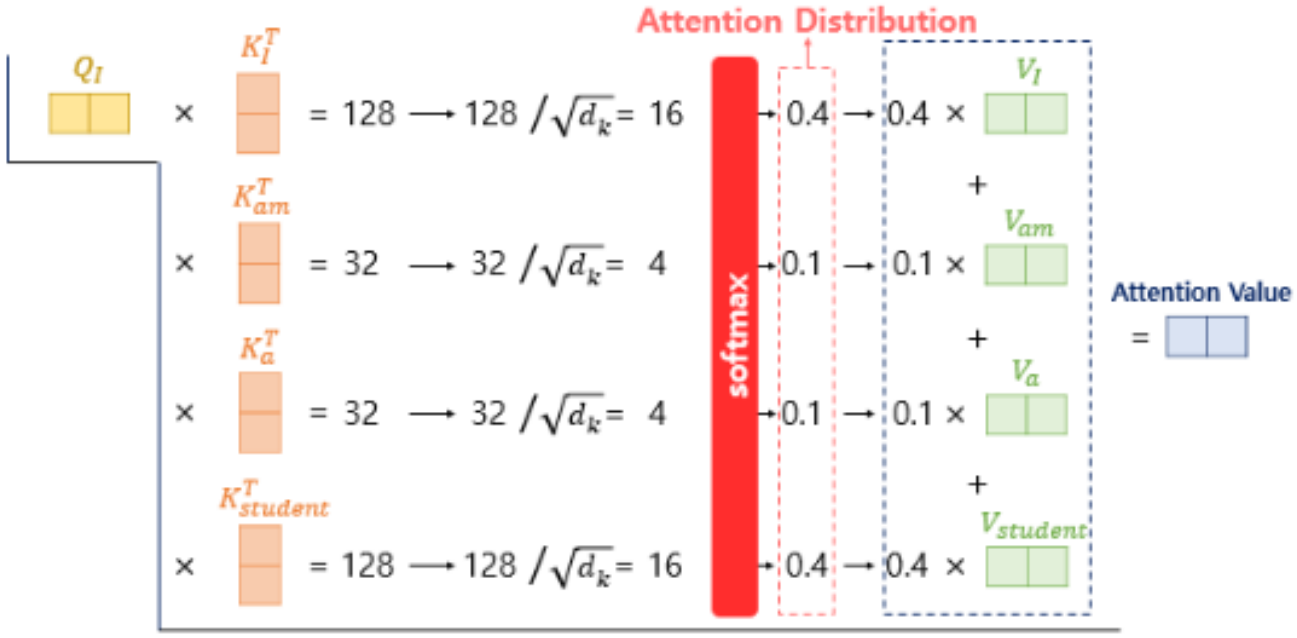
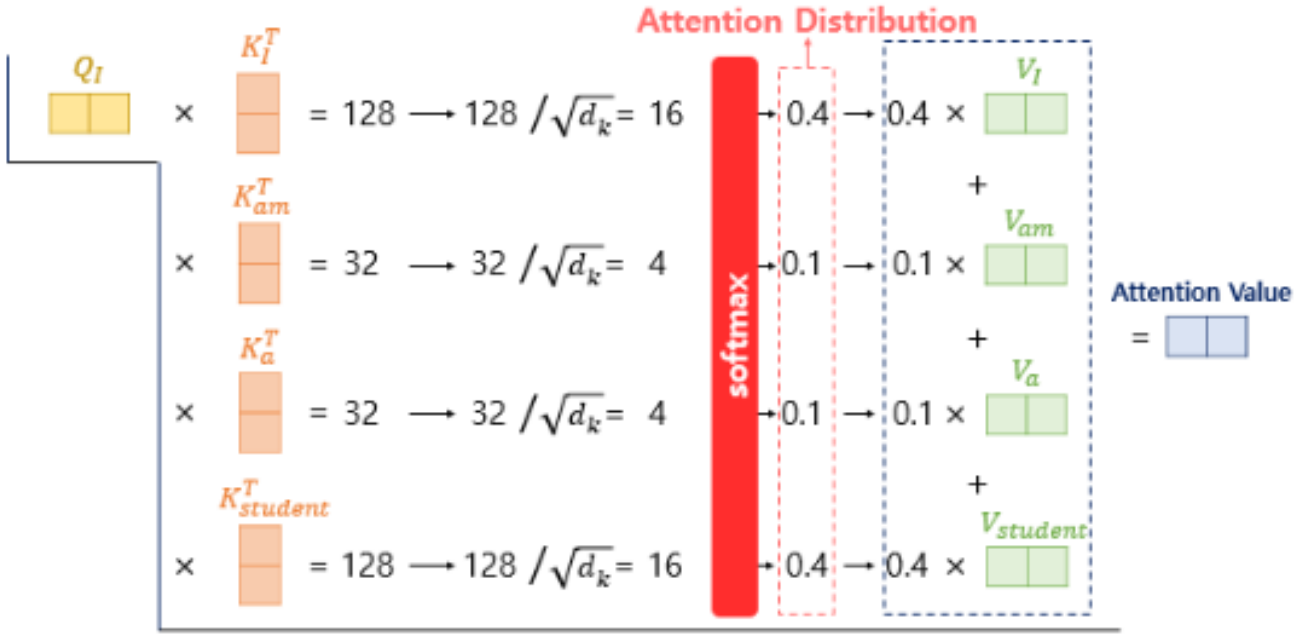
  - 트랜스포머에서는 두 벡터의 내적값을 스케일링하는 값으로 d_k에 루트를 씌운 $\sqrt{d_k}$ 사용함.



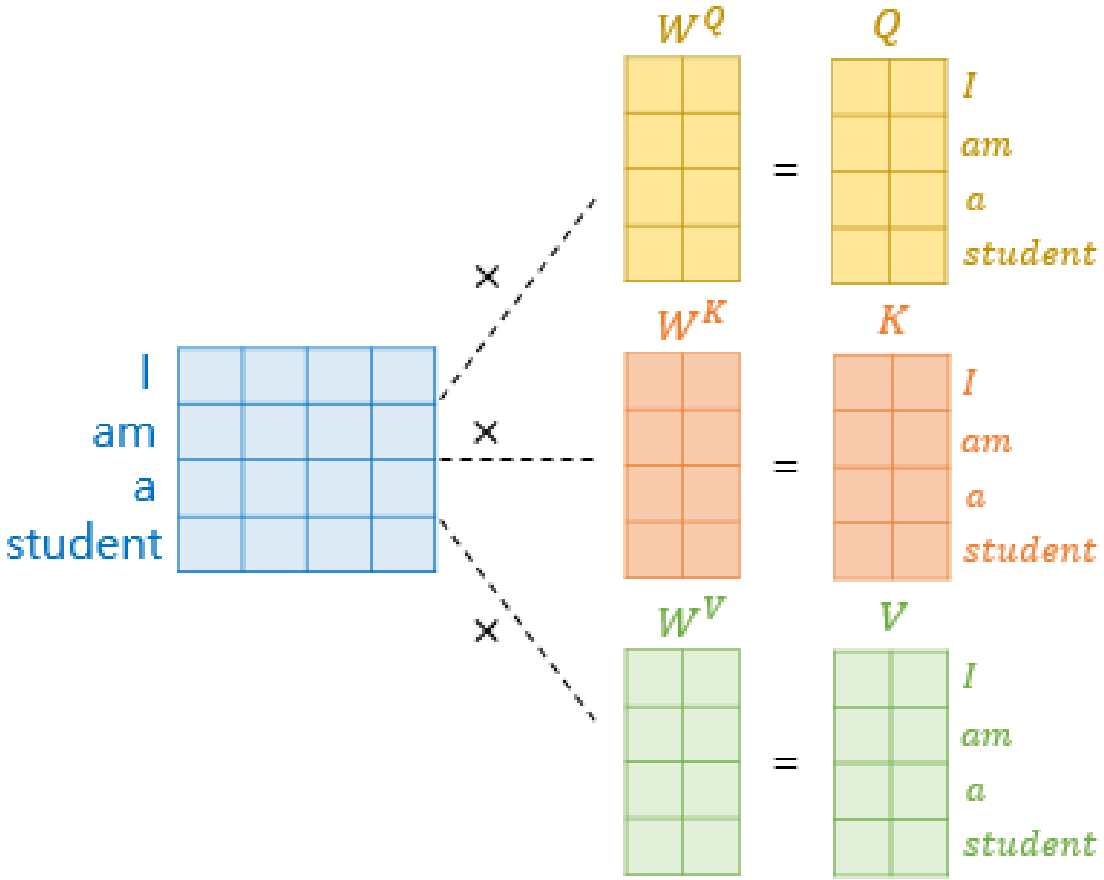
2.1 Self-Attention

- Scaled dot product Attention
  - Attention Value가 결국 Context Vector



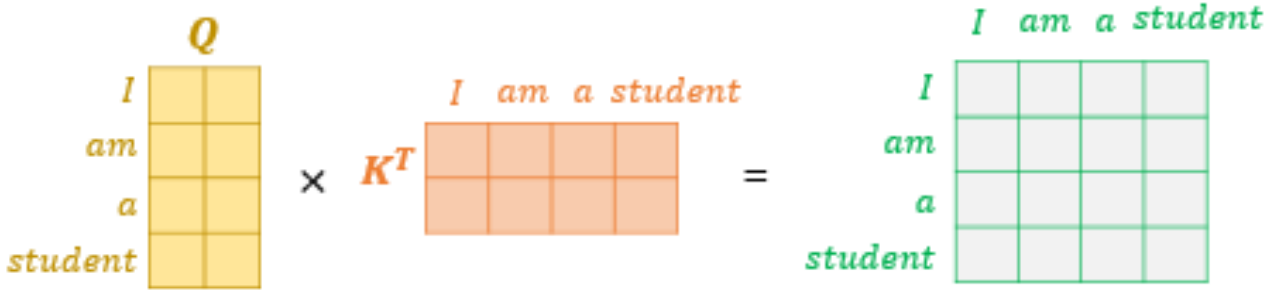
2.1 Self-Attention

- Parallelization

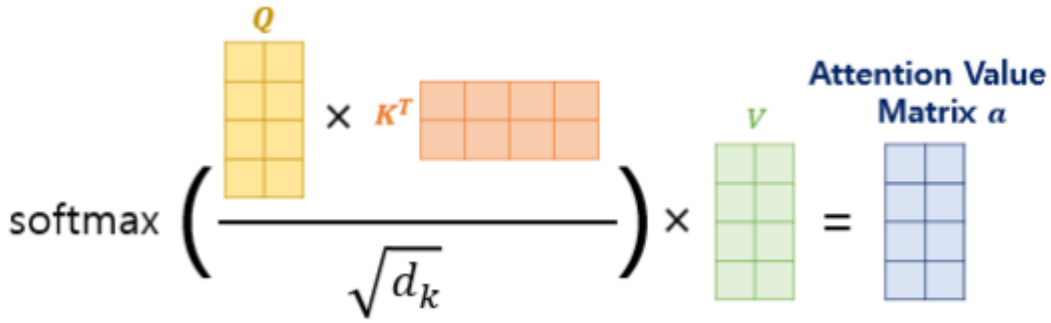


2.1 Self-Attention

- Attention Score
  - Self-Attention으로 Attention Score행렬을 구한다.

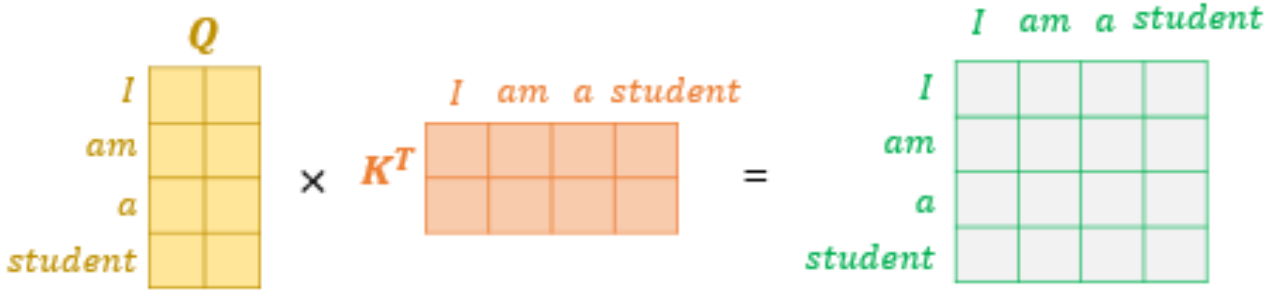


- Attetion Value
  - 스코어 행렬로 어텐션 분포를 구하고, 이를 사용하여 모든 단어에 대한 어텐션 값을 구한다.

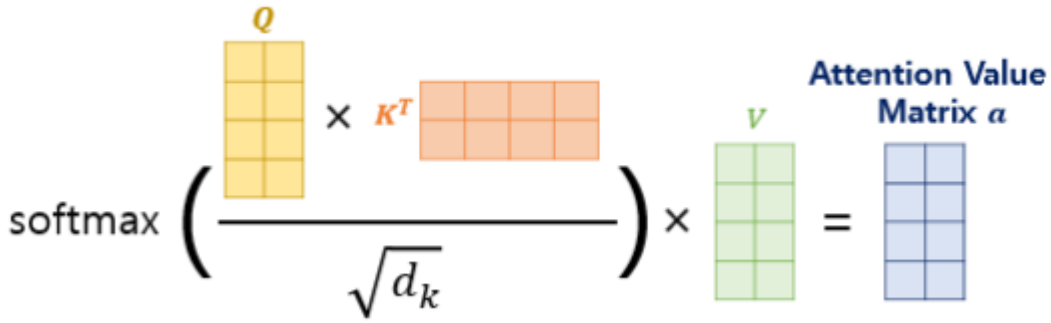


2.1 Self-Attention

- Attention Score
  - Self-Attention으로 Attention Score행렬을 구한다.



- Attetion Value
  - 스코어 행렬로 어텐션 분포를 구하고, 이를 사용하여 모든 단어에 대한 어텐션 값을 구한다.



2.1 Self-Attention

- Matrix 크기 정리

Q와 K의 크기 = $\mathbf{d}_k$, -> shape = (문장길이, d_k)

V의 크기 = $\mathbf{d}_v$, , -> shape = (문장길이, d_v)

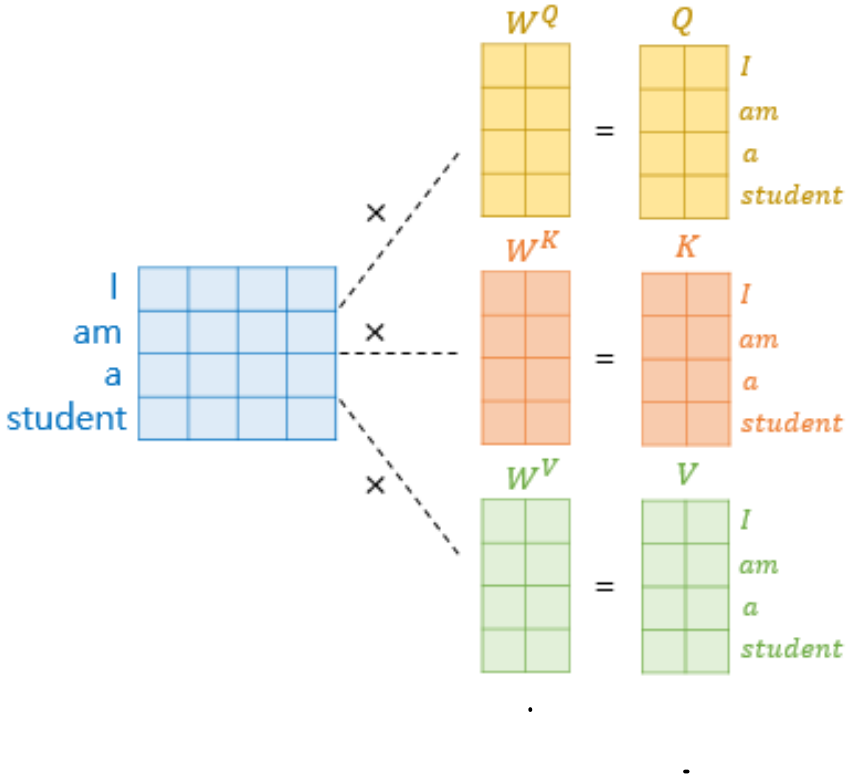
Wq와 Wk -> (d_{model}, d_k)

Wv -> (d_{model}, d_v)

논문에서는 d_{model}/ num_heads = d_k = d_v

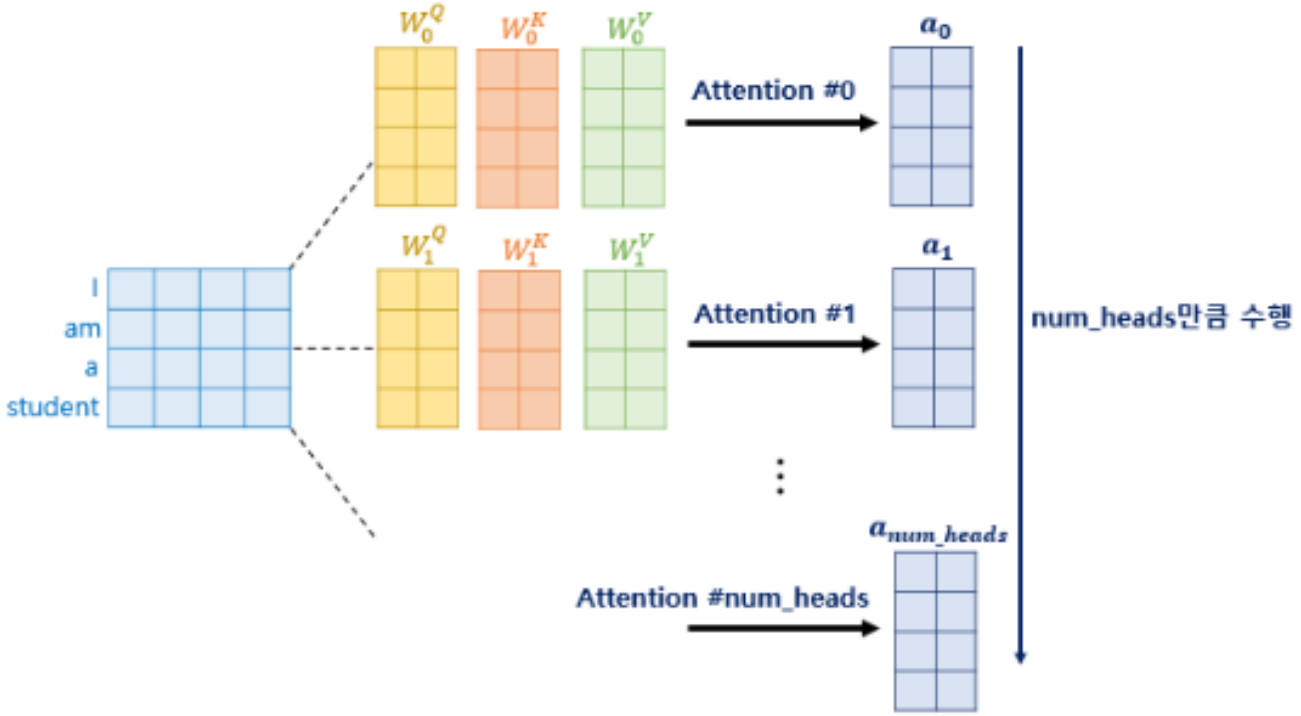
결과적으로 Attention(Q,K,V) = a(seq_len, d_v)

입력 데이터의 shape와 동일하다!



2.2 Multi-head Attention

- 왜 임베딩 차원에 num_heads로 나눴냐!
- Head수 만큼 각각의 어텐션을 따로 해준다.
- 각 head마다 Wq, Wk, Wv 값은 다르다.



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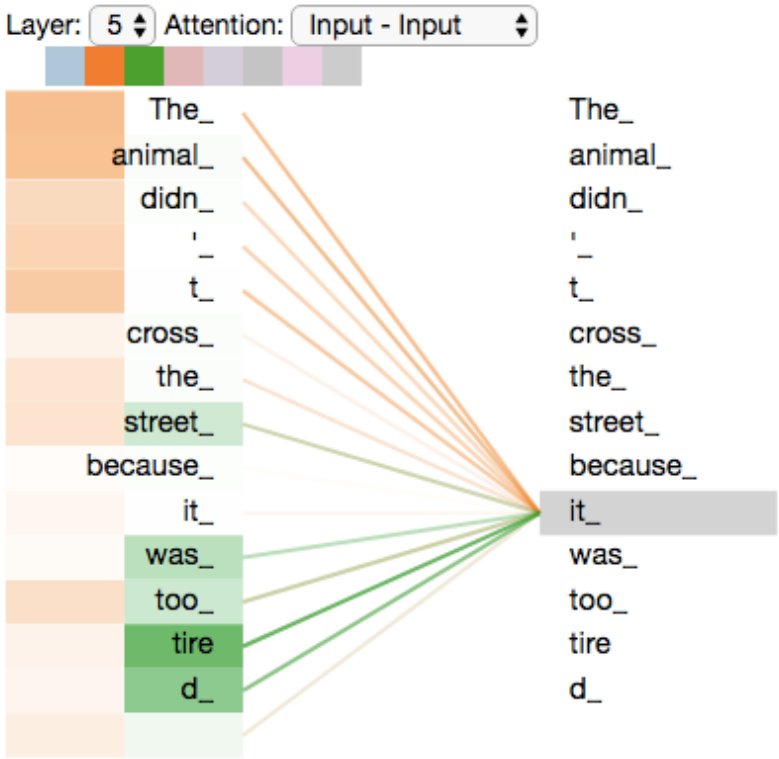
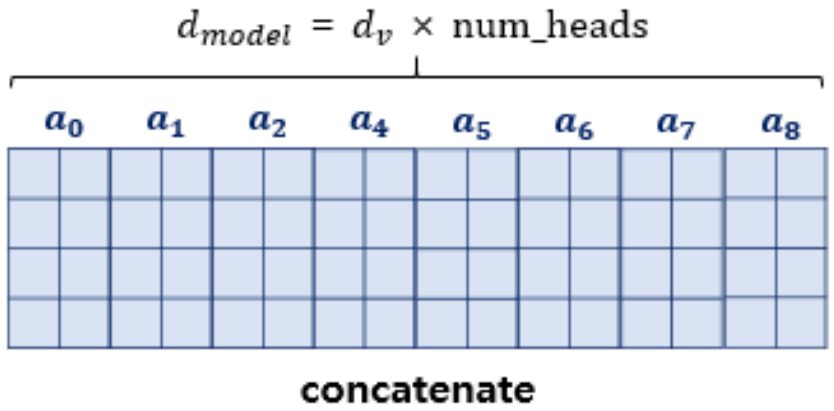
- Head수 만큼 각각의 어텐션을 따로 해준다.
- 각 head마다 Wq, Wk, Wv 값은 다르다.

-> 시각의 다양성



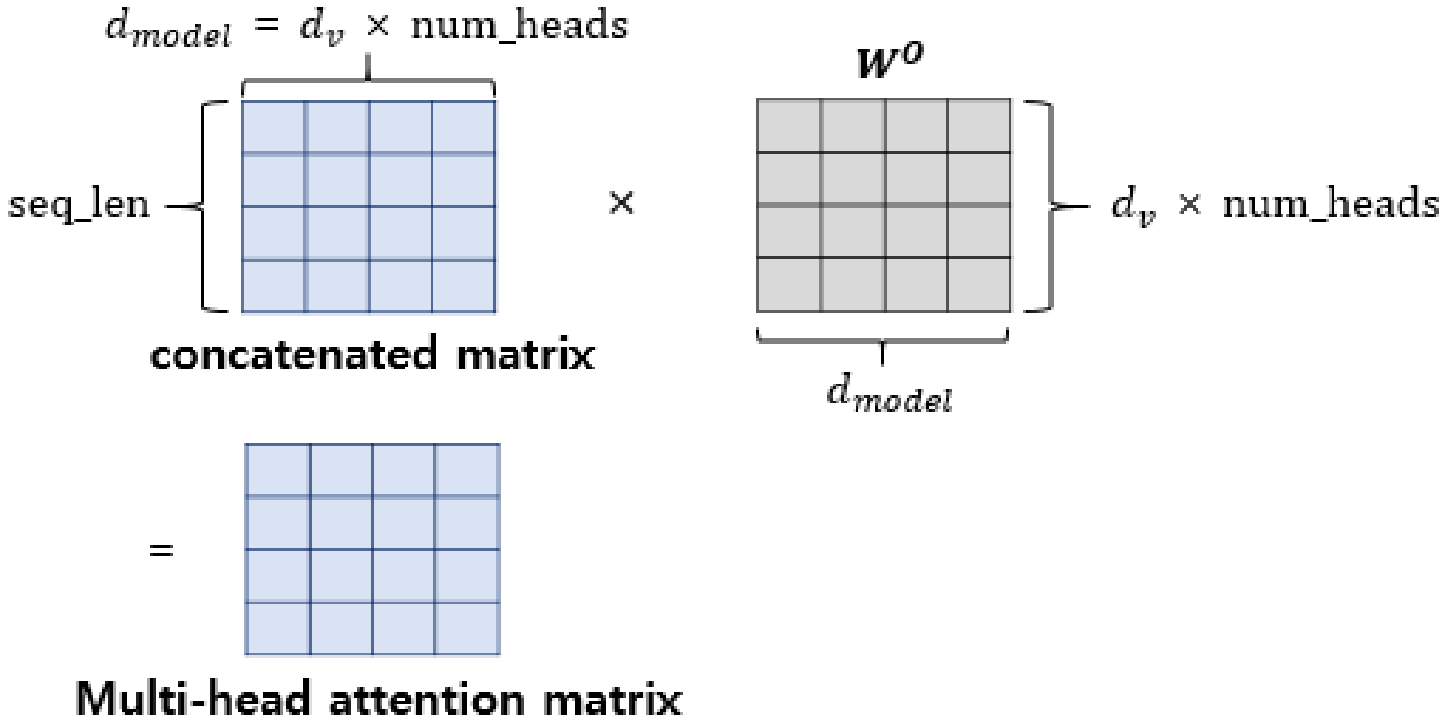
2.2 Multi-head Attention

- 병렬 어텐션 후 모든 어텐션 헤드를 연결(Concatenate)
- Concat 이후 shape = (seq_len, d_{model})



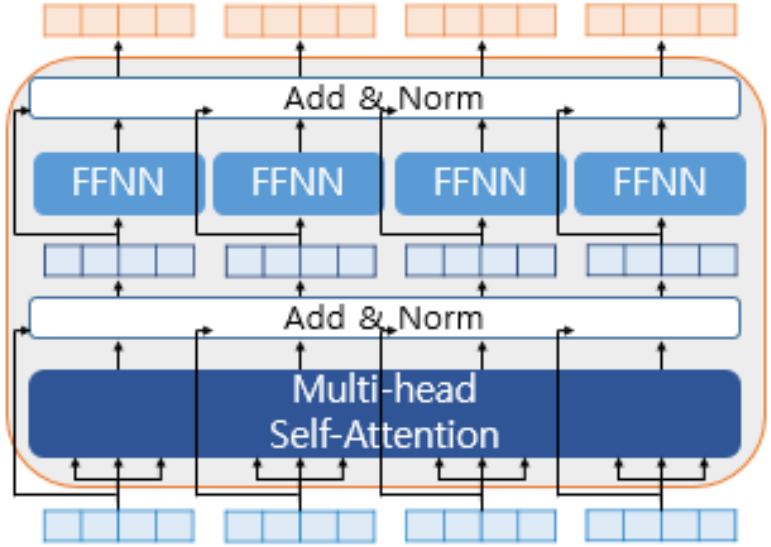
2.2 Multi-head Attention

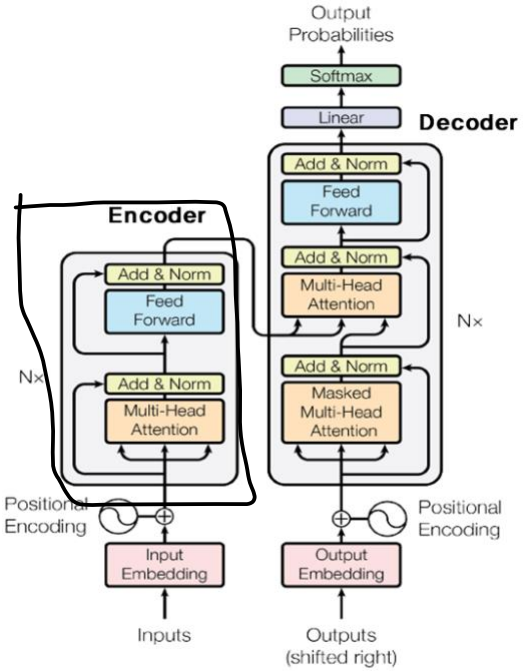
- Concatenated Matrix에 또 다른 가중치 행렬 Wo를 곱해서 최종 결과물이 나온다.



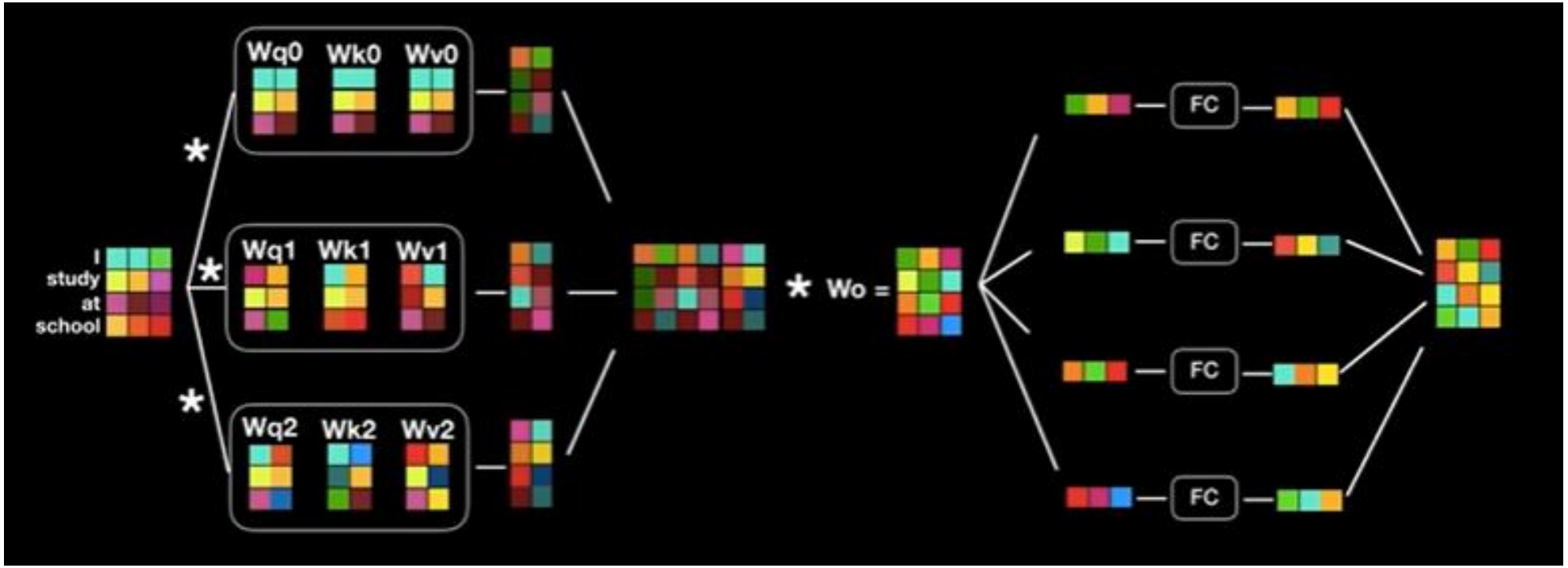
2.3 Residual connection

- Encoder에는 추가적으로 Residual Connection을 사용한다.
- Why? Layer를 거칠수록 gradient가 사라지는 vanishing gradient문제 완화



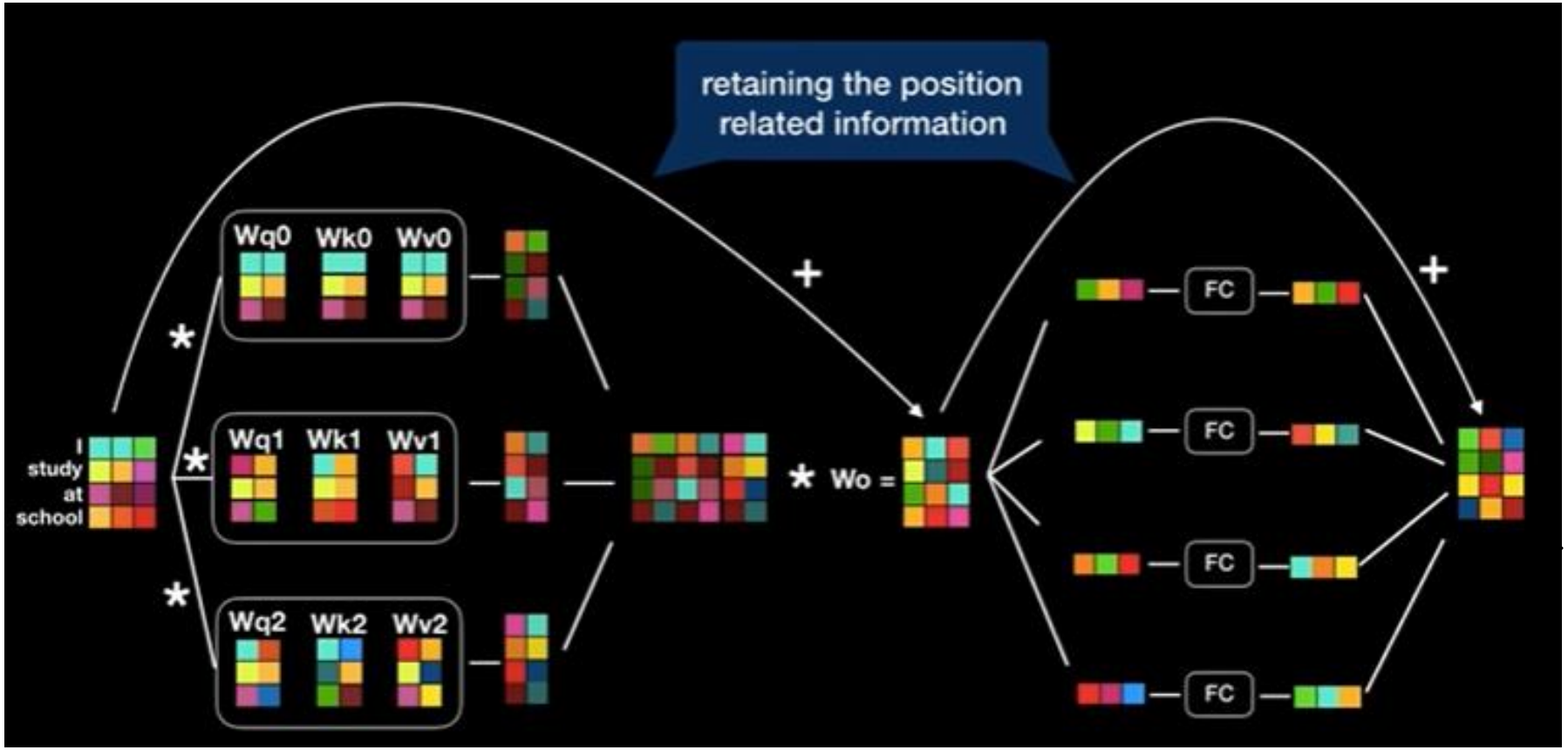


2.3 Residual connection



- https://www.youtube.com/watch?v=mxGCEWOxfe8

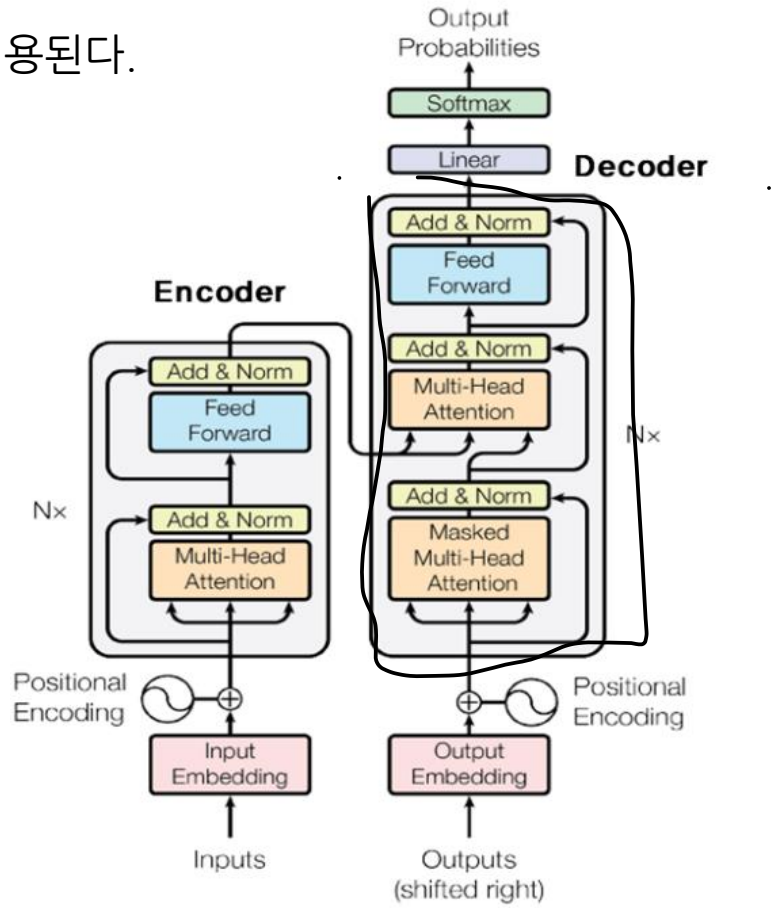
2.3 Residual connection



3. Decoder

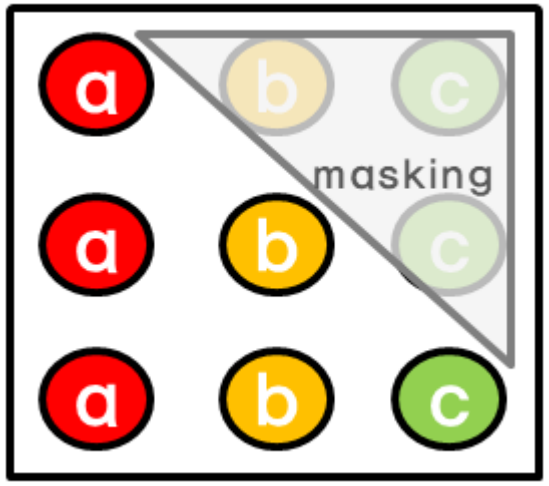
- 비슷한 구조이지만, Encoder의 Self-Attention과는 약간 다른 방법이 적용된다.
  - Masking -> position i 보다 이후에 있는 position에 attention을 주지 않음

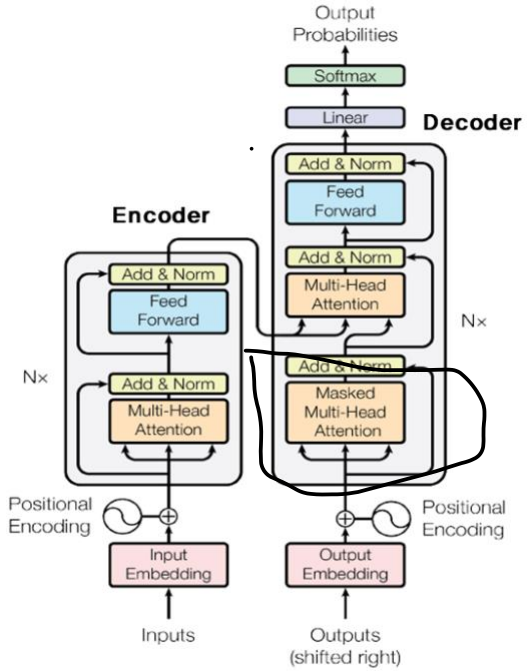
- 1층에는 Masked Multi-Head Attention
- 2층에는 Encoder에서 온 Key, Value와 Decoder의 query가 input
  - '지금 decoder에서 이런 값이 나왔는데 무엇이 output이 돼야 할까?'
- 3층에는 FFNN
- 모두 Residual Connection 존재



3.1 Masked Self-Attention

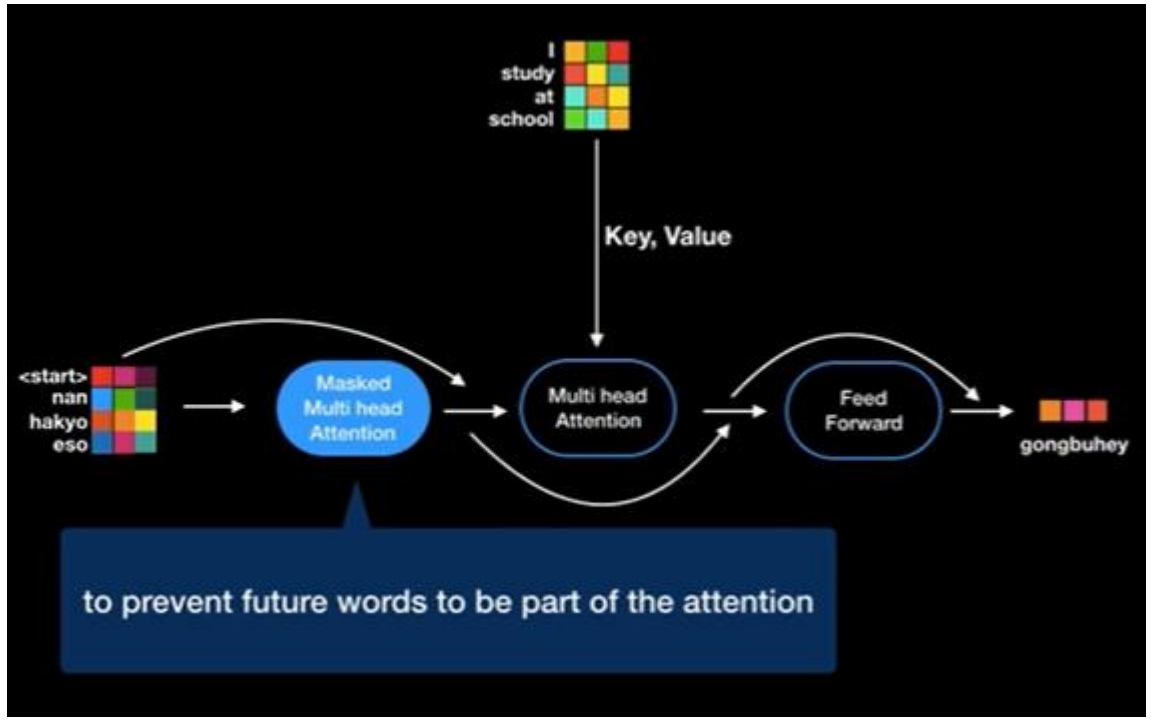
- Decoder에서는 i번째 ouput을 다시 i+1번째 input으로 사용하는 auto-regressive 한 특성을 유지하기 위해, masking out된 attention을 적용한다.
- How? Attention(Q,K,V)에서 softmax의 인풋값을 -무한대로 설정

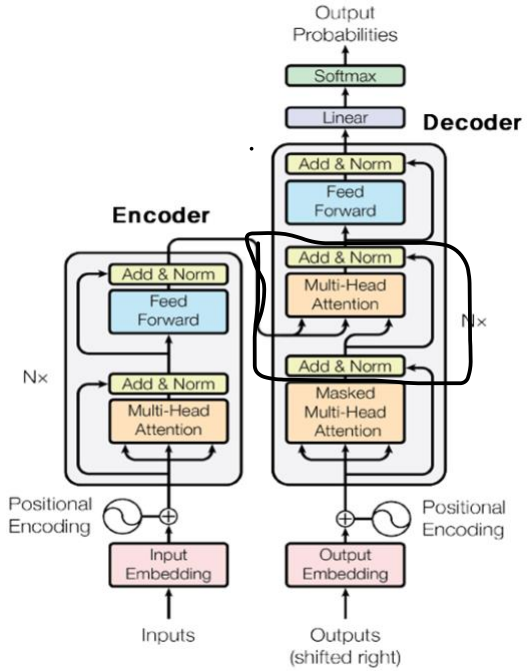




3.2 Decoder flow

- Decoder의 흐름 예시





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