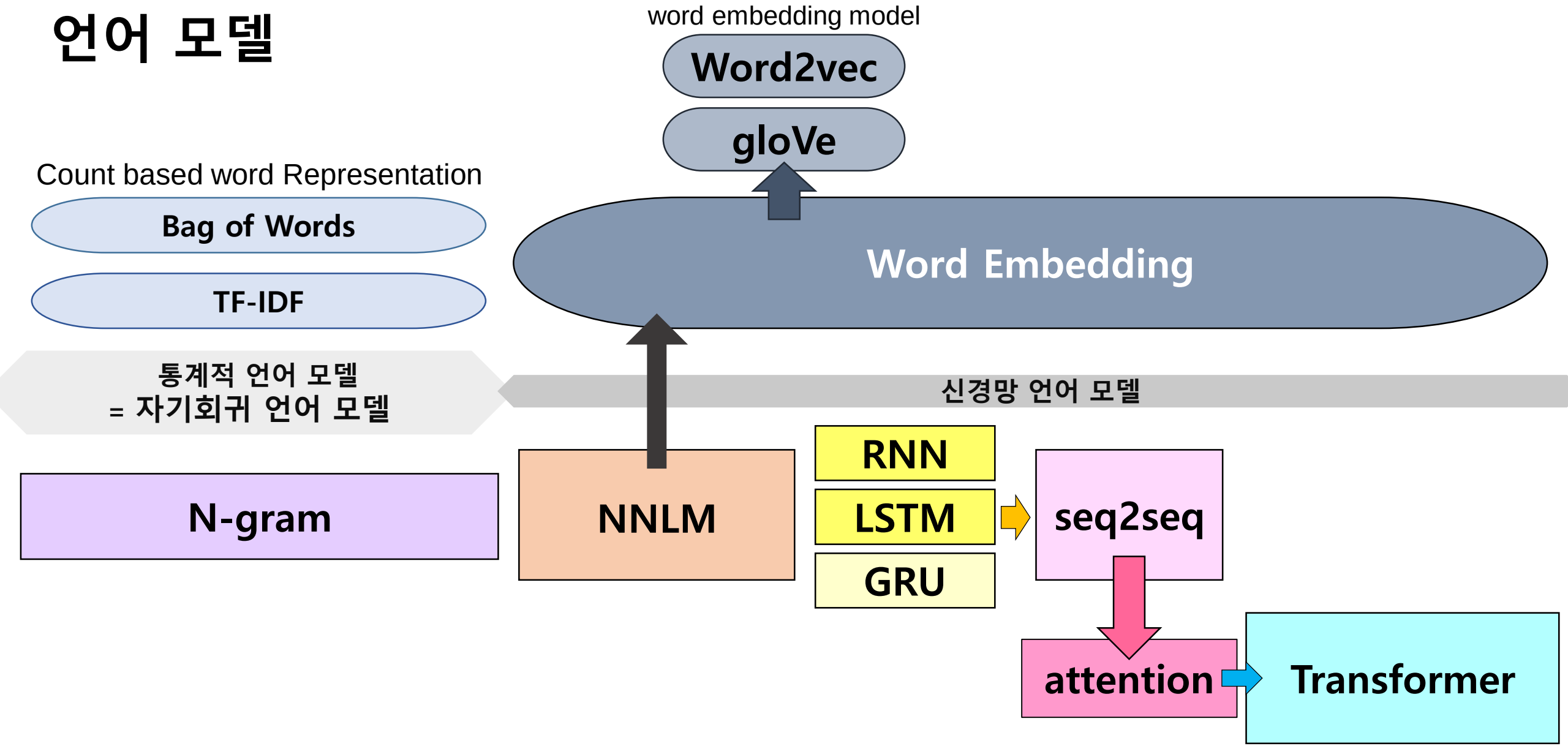
seq2seq와 Attention

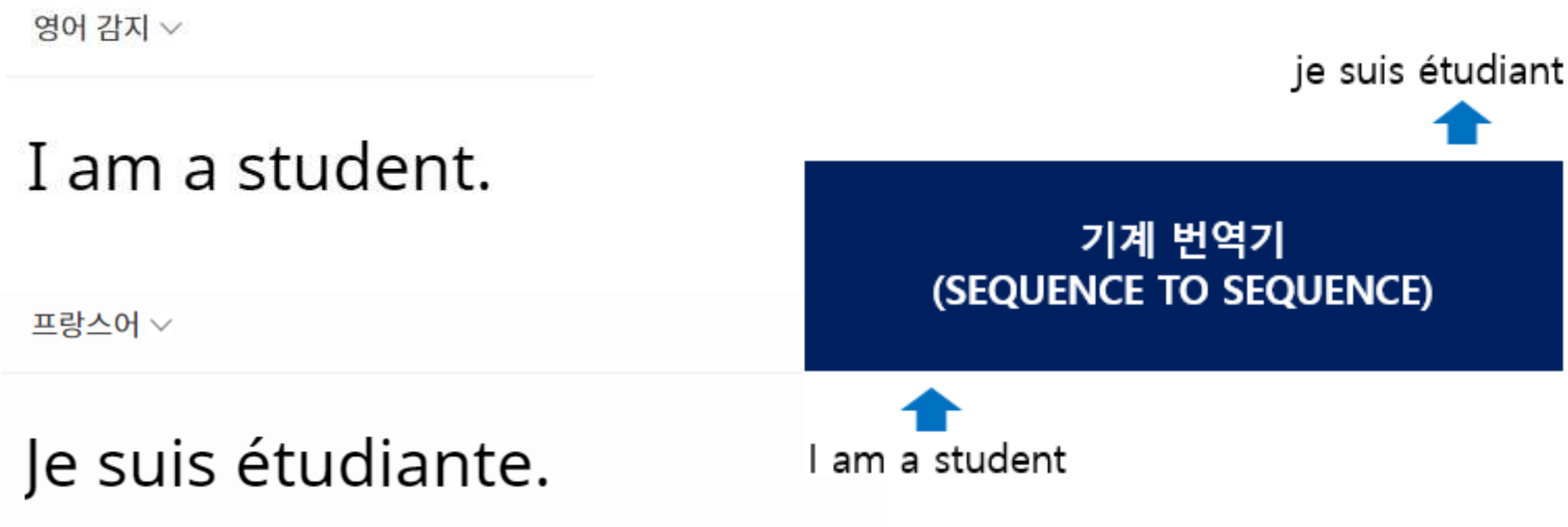
23.07.13 유하영

언어 모델

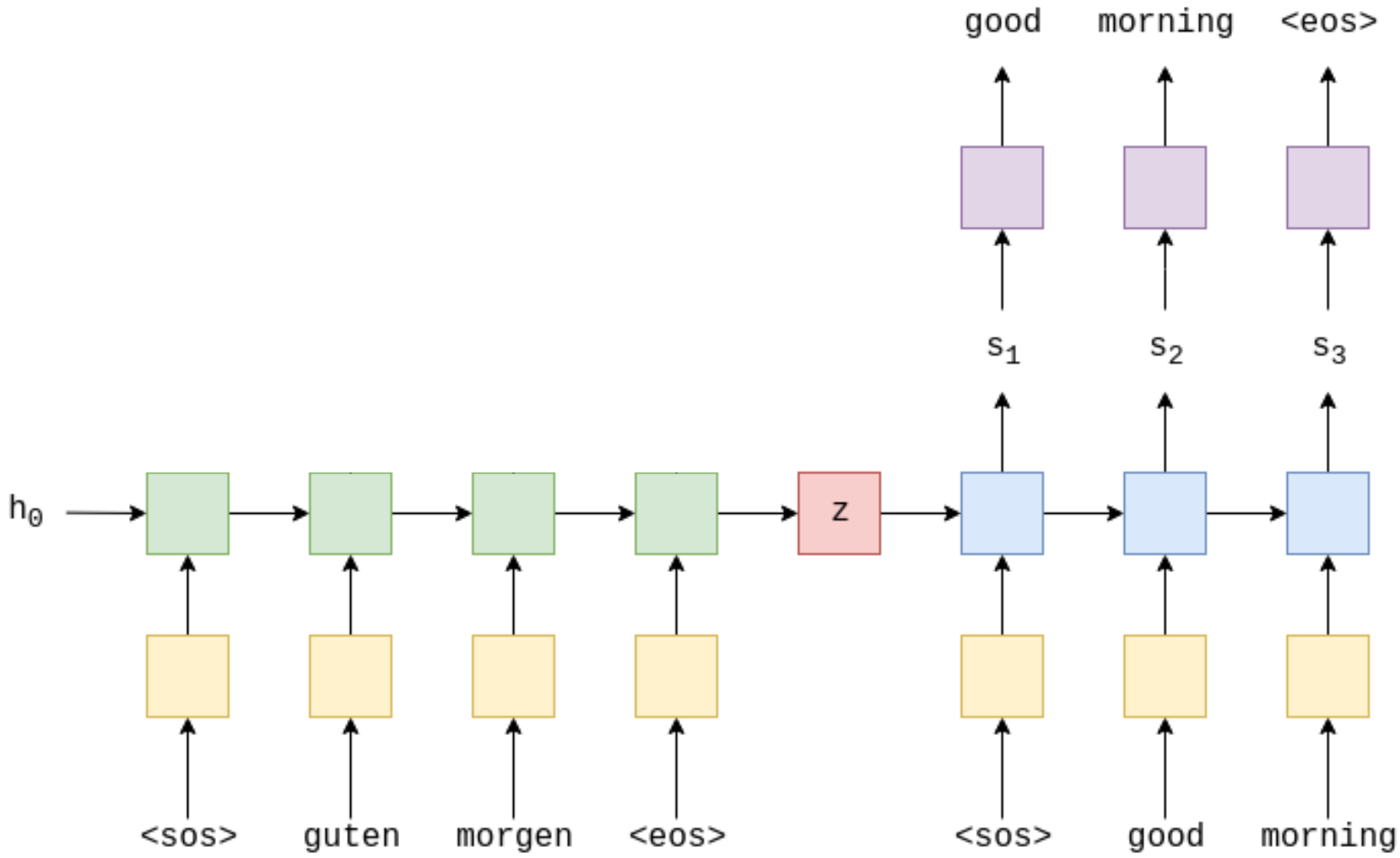

word embedding model
Word2vec
gloVe
Count based word Representation
Bag of Words
TF-IDF
Word Embedding
통계적 언어 모델
= 자기회귀 언어 모델
신경망 언어 모델
N-gram
NNLM
RNN
LSTM
GRU
seq2seq
attention
Transformer

seq2seq

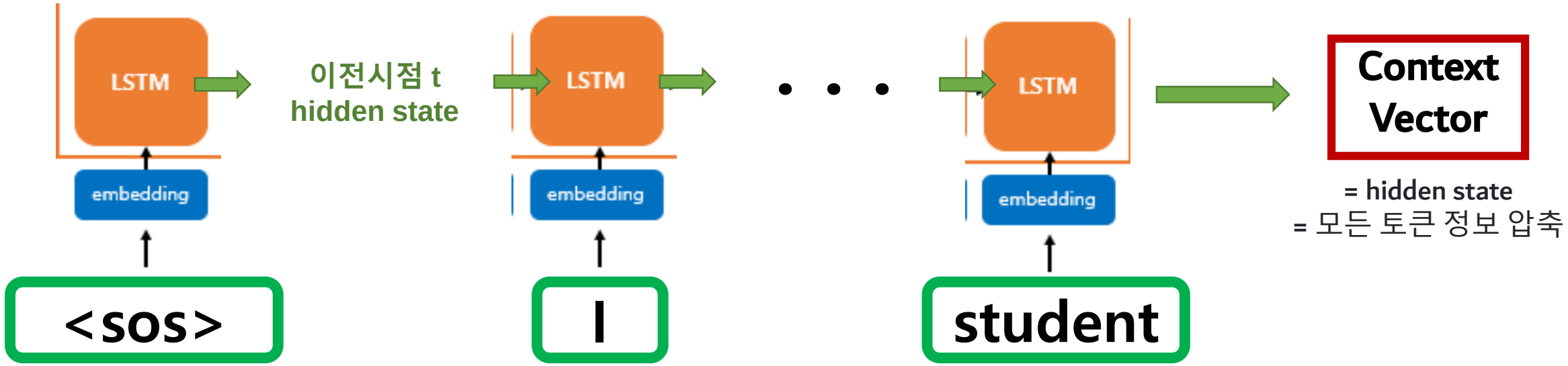
: 2개의 **RNN**을 연결해서 사용하는 **Encoder, Decoder** 구조



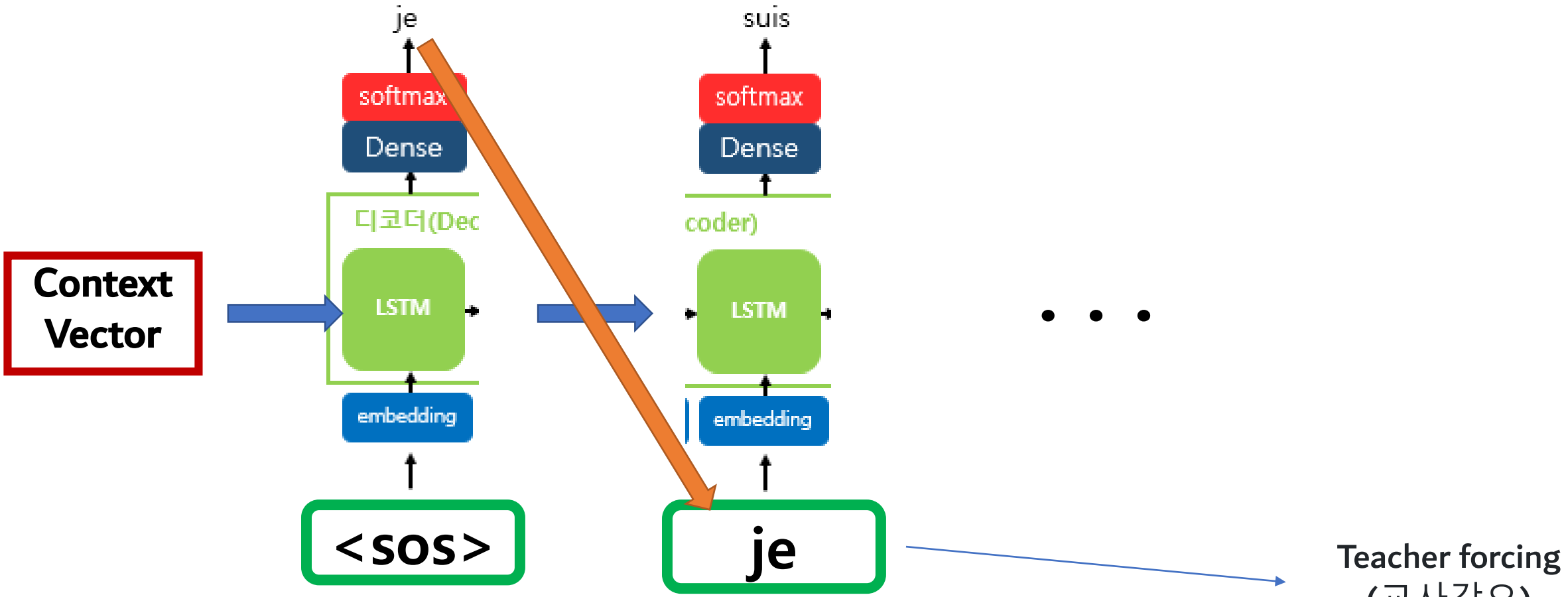
seq2seq

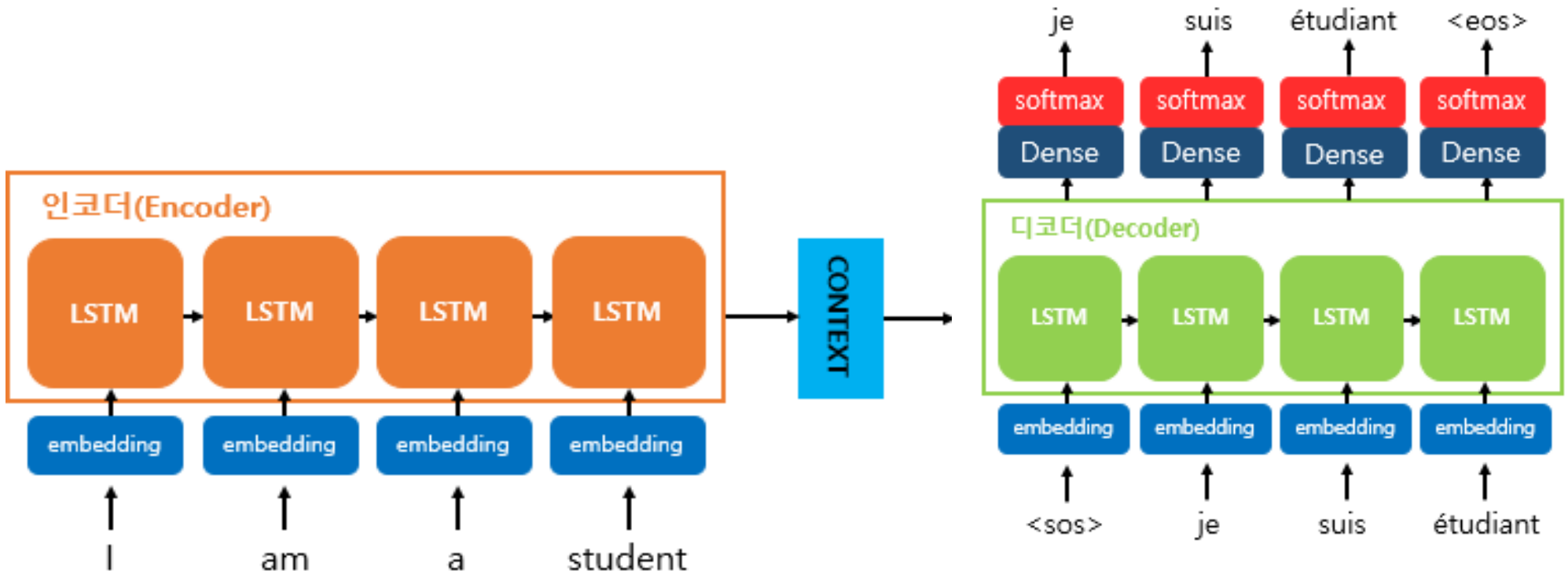

good
morning
<eos>
s_1
s_2
s_3
h_0
z
<sos>
guten
morgen
<eos>
<sos>
good
morning
Encoder
Decoder

Encoder


LSTM
embedding
<sos>
이전시점 t
hidden state
LSTM
embedding
I
LSTM
embedding
student
Context
Vector
= hidden state
= 모든 토큰 정보 압축
시점 t
시점 t+1

Decoder


je
suis
softmax
Dense
디코더(Dec
coder)
LSTM
embedding
Context Vector
<sos>
je
Teacher forcing
(교사강요)
시점 t
시점 t+1


인코더(Encoder)
LSTM
LSTM
LSTM
LSTM
embedding
embedding
embedding
embedding
I
am
a
student
CONTEXT
디코더(Decoder)
LSTM
LSTM
LSTM
LSTM
embedding
embedding
embedding
embedding
<sos>
je
suis
étudiant
softmax
softmax
softmax
softmax
Dense
Dense
Dense
Dense
je
suis
étudiant
<eos>

seq2seq의 한계

입력 시퀀스의 모든 정보를 **context vector**에 압축하게 되면

정보손실 및 번역품질이 떨어질 가능성 존재

Attention mechanism

time step마다 **Decoder**에서

전체 입력문장(Encoder) 다시한번 참고

뉴진스 - attention

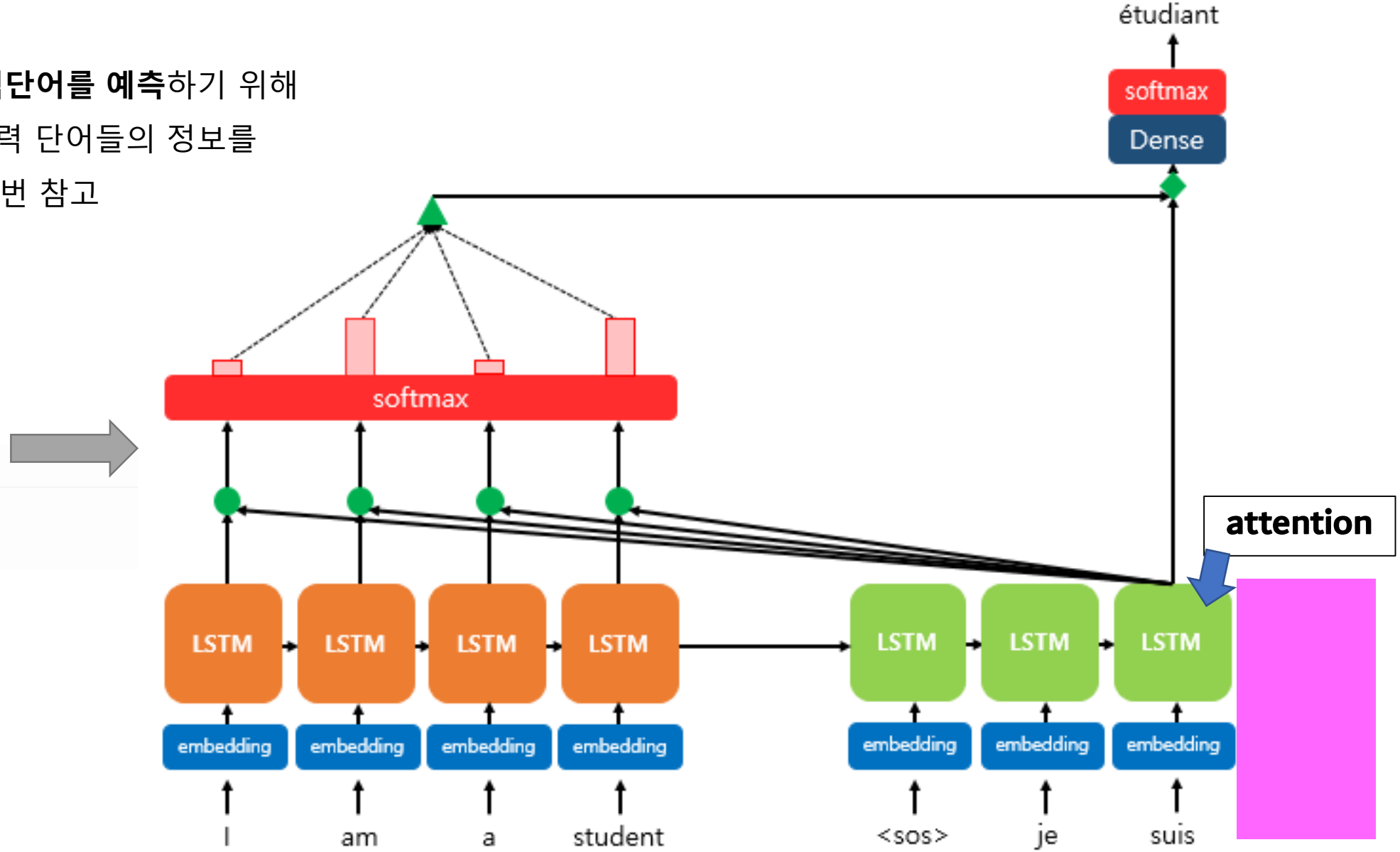
Decoder의 **3번째 출력단어를 예측**하기 위해
Encoder의 모든 입력 단어들의 정보를
다시 한번 참고

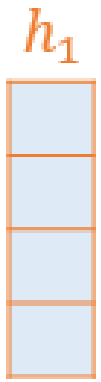
영어 감지

I am a student.

프랑스어

Je suis étudiante.





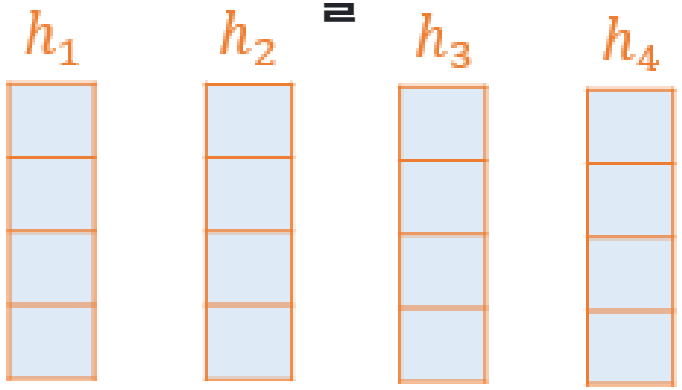
h_i : 시점 t=1에서의 Encoder 은닉상태

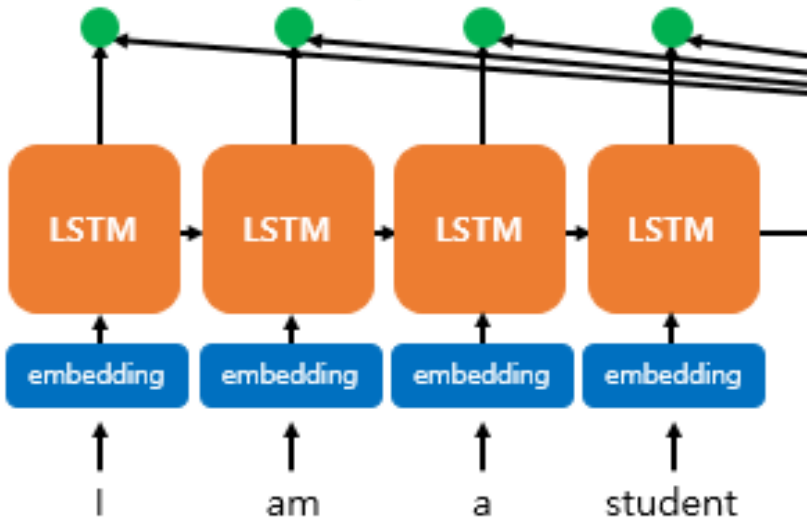
임베딩 벡터 변환

시퀀스 단어 입력

시점(t) = 1

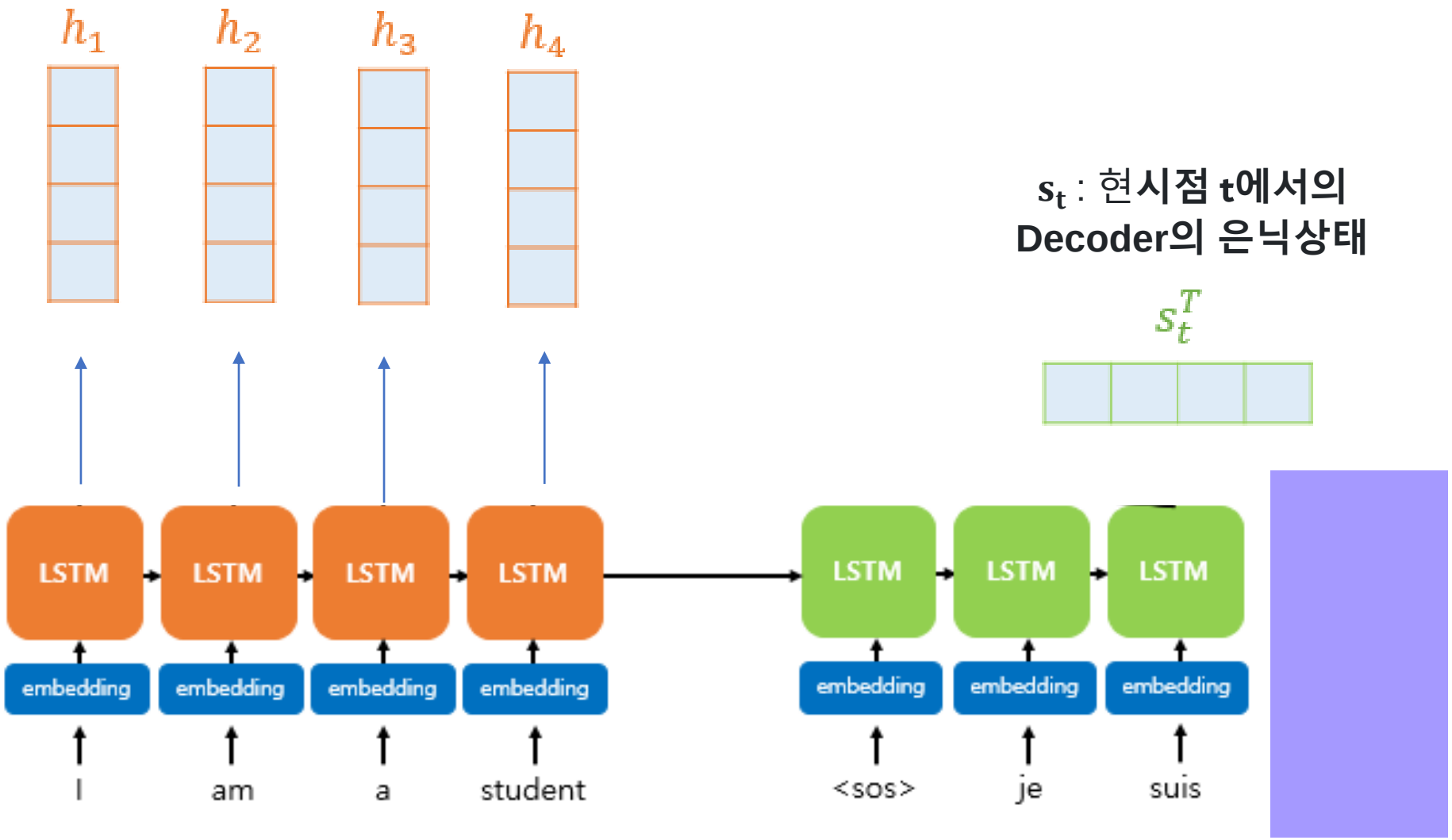
각 시점에서의 **Encoder 은닉상태 값들**





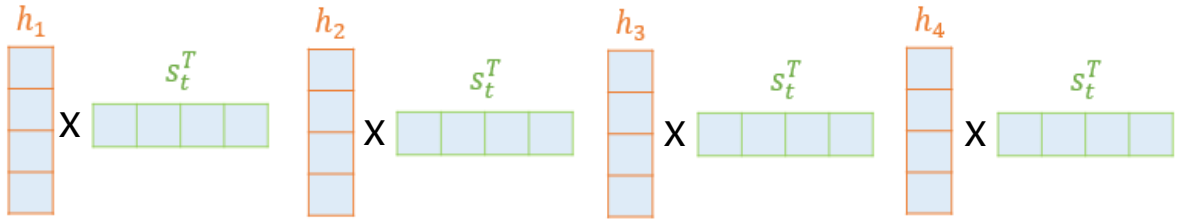
시점(t) = 1

s_t : 현시점 t에서의
Decoder의 은닉상태



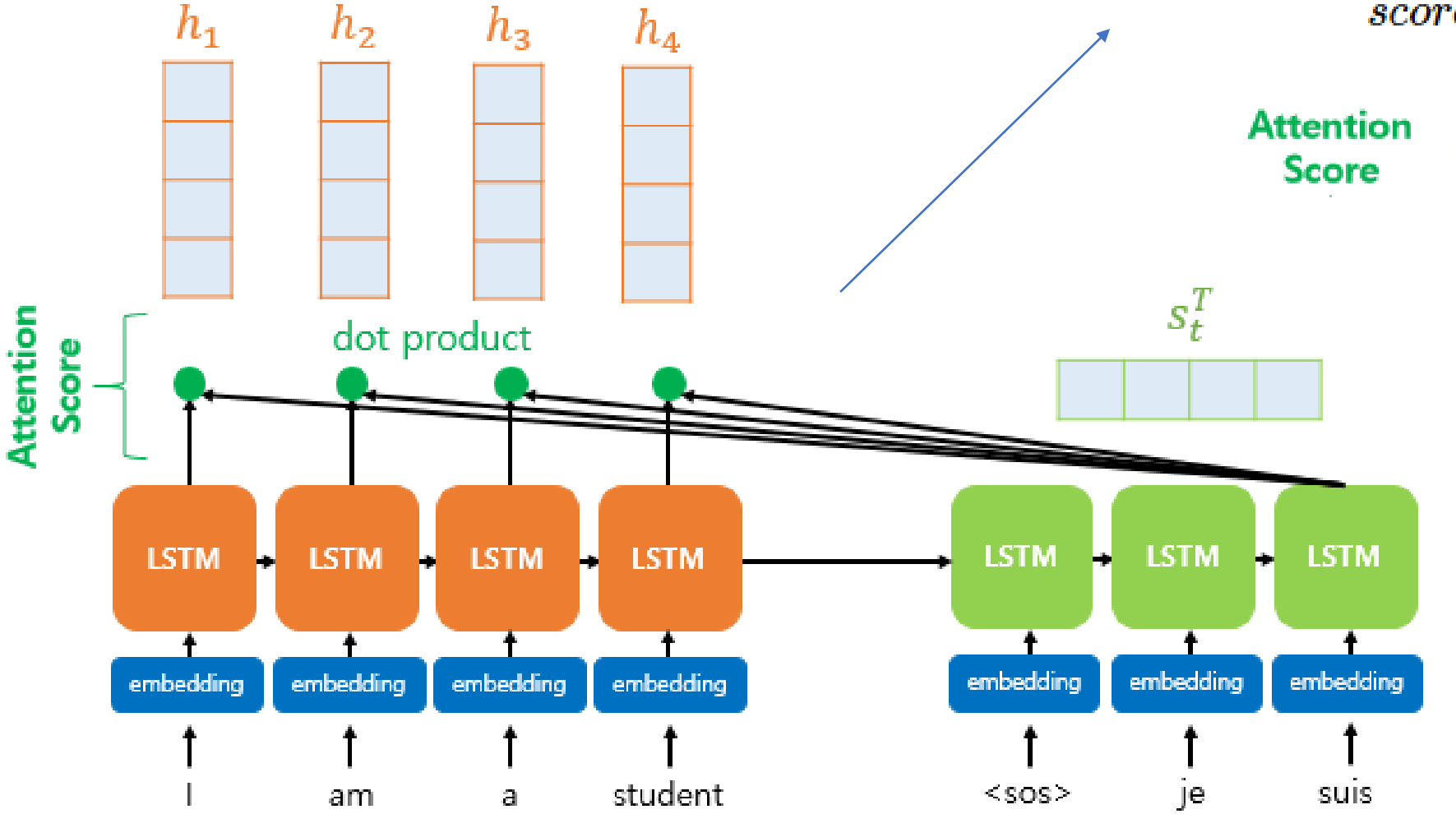
1) Attention score

: 단어 간 유사도 분포



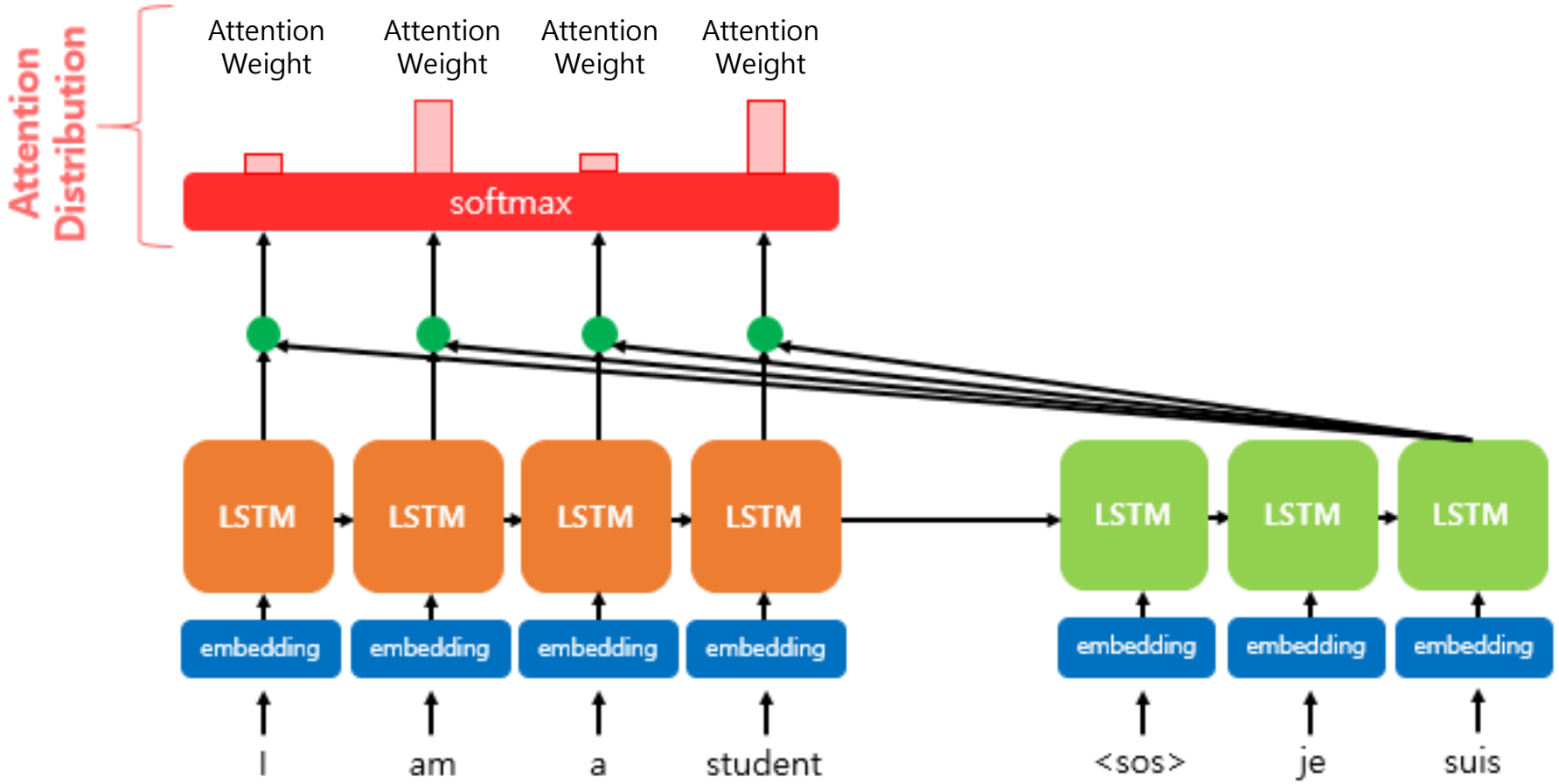
$$score(s_t,\ h_i) = s_t^T h_i$$

Attention Score $e^t = [s_t^T h_1, \ldots, s_t^T h_N]$



2) Attention Distribution

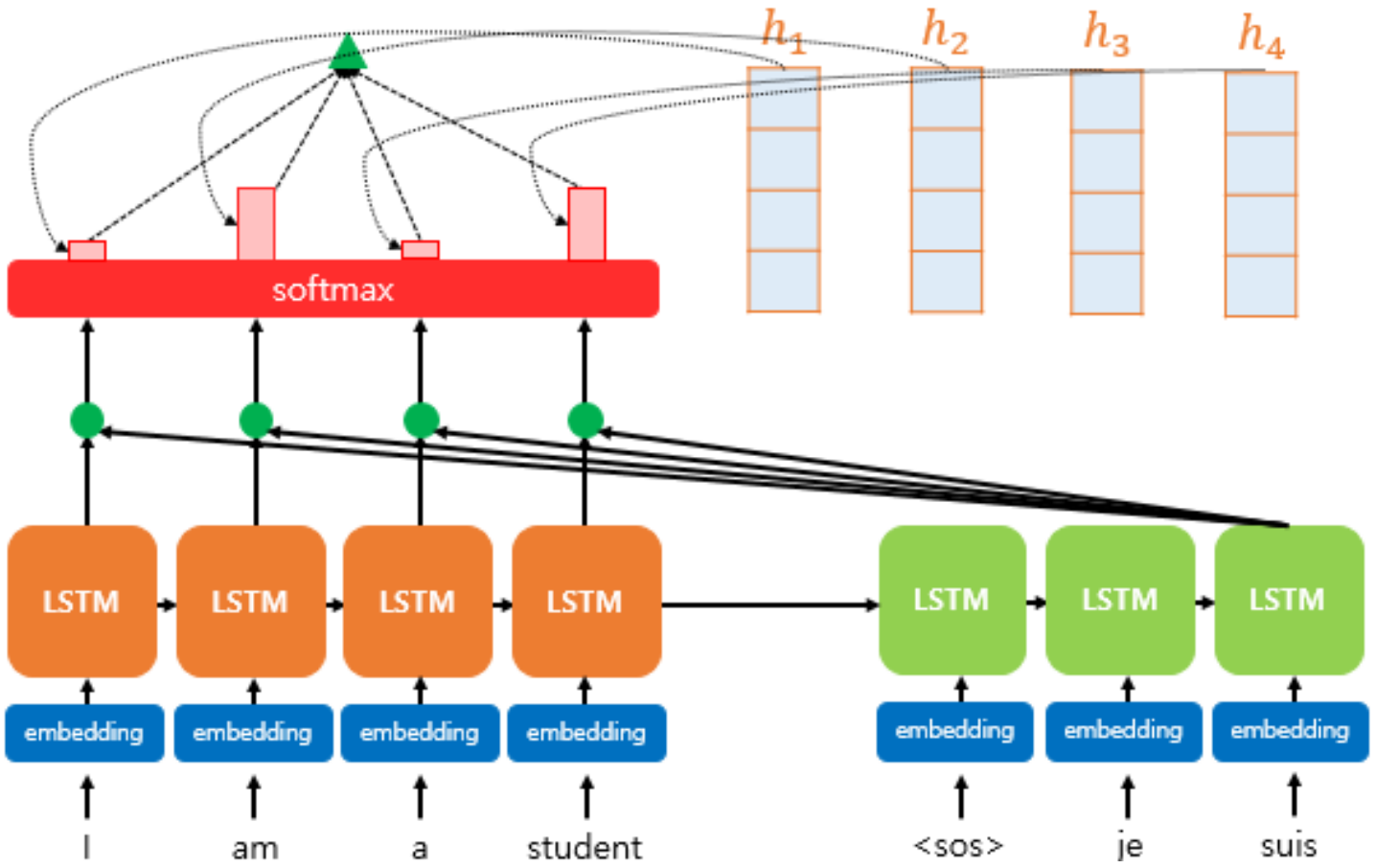
$$\alpha^t = softmax(e^t)$$



3) 각 인코더의 어텐션 가중치와 은닉상태를 가중 합하여 **Attention value**를 구하기

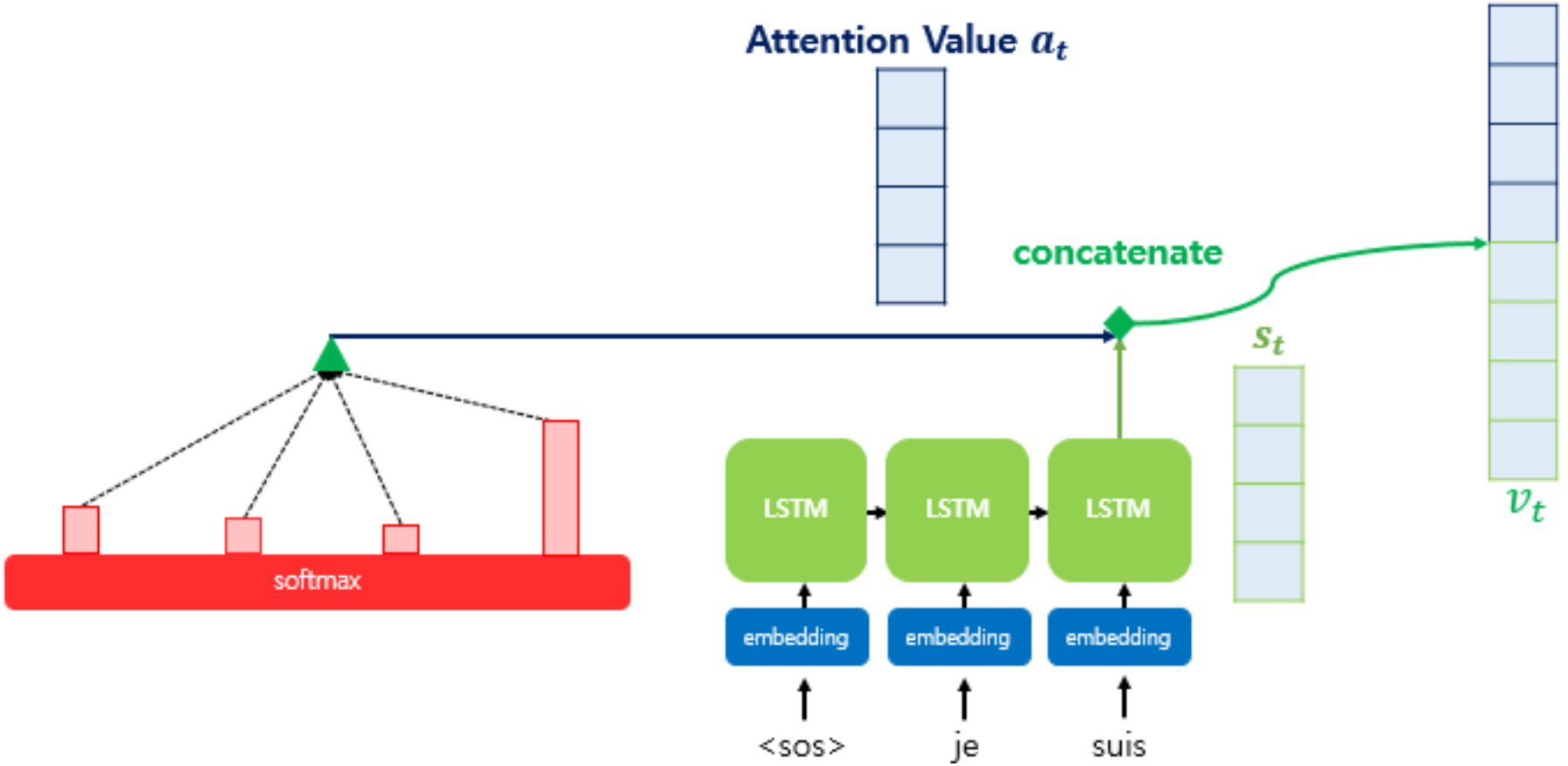
= 보정**된 컨텍스트 벡터**

α^t h_i



$$a_t = \sum_{i=1}^{N} \alpha_i^t h_i$$

4) 어텐션 값과 t 시점의 디코더 은닉상태를 연결 (**concatenate**)



가중치 정보 a_t concatenate s_t = v_t 디코더 자체의 정보

디코더와 인코더의 정보와 상태를 동시에 고려할 수 있게 됨

seq2seq의 성능을 보정하기 위한 목적

-> 어텐션 스스로가 기존의 seq2seq을 대체하는 방법

->Transformer