Seq2seq

한양대학교 AILAB 박소영

01. Translator

번역기를 만들어보자

나는 널 사랑해

I love you

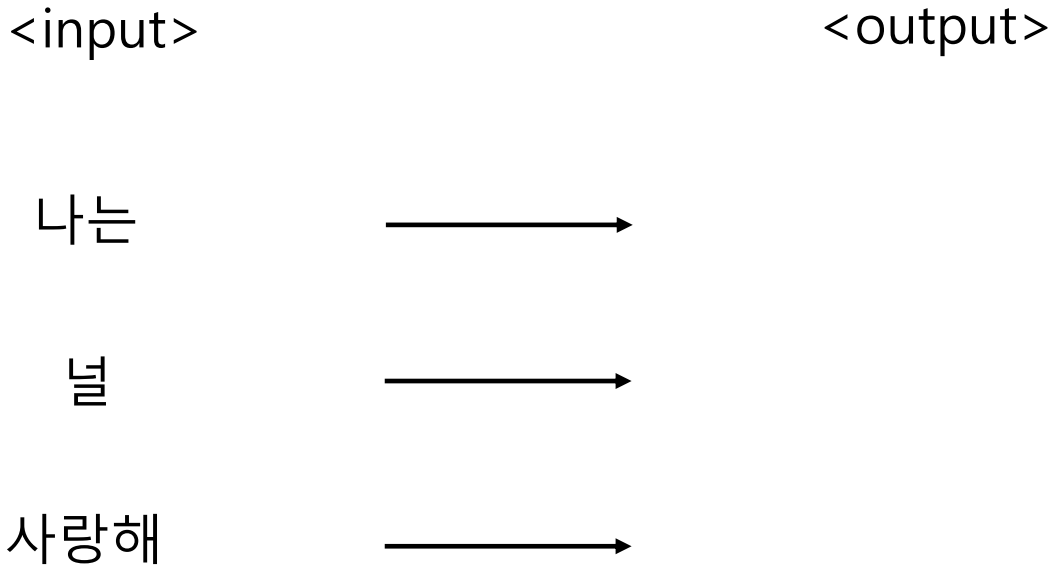
我愛你

愛してる

je t'aime

01. Translator

번역기를 만들어보자



01. Translator

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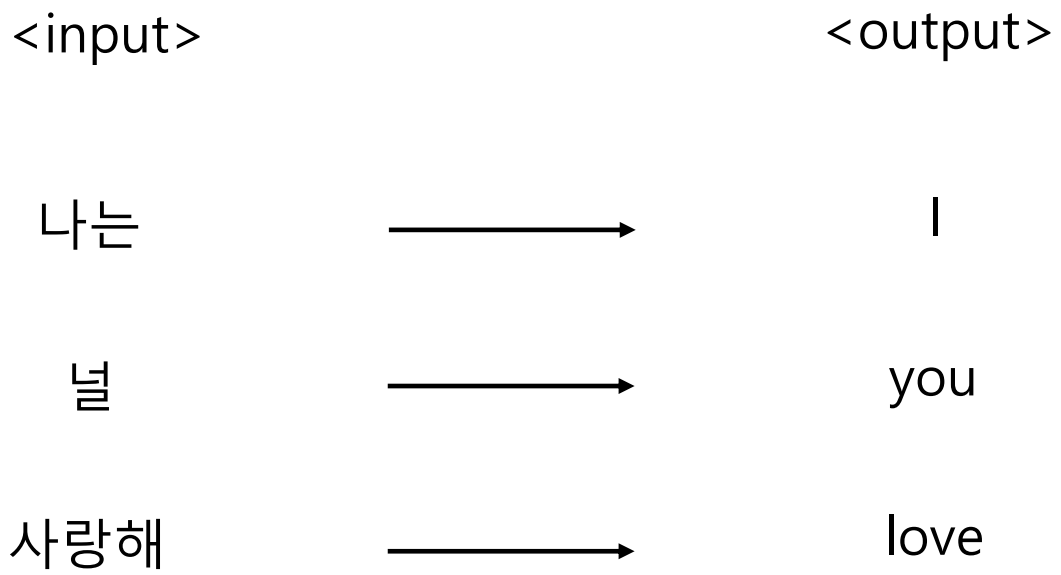

01. Translator

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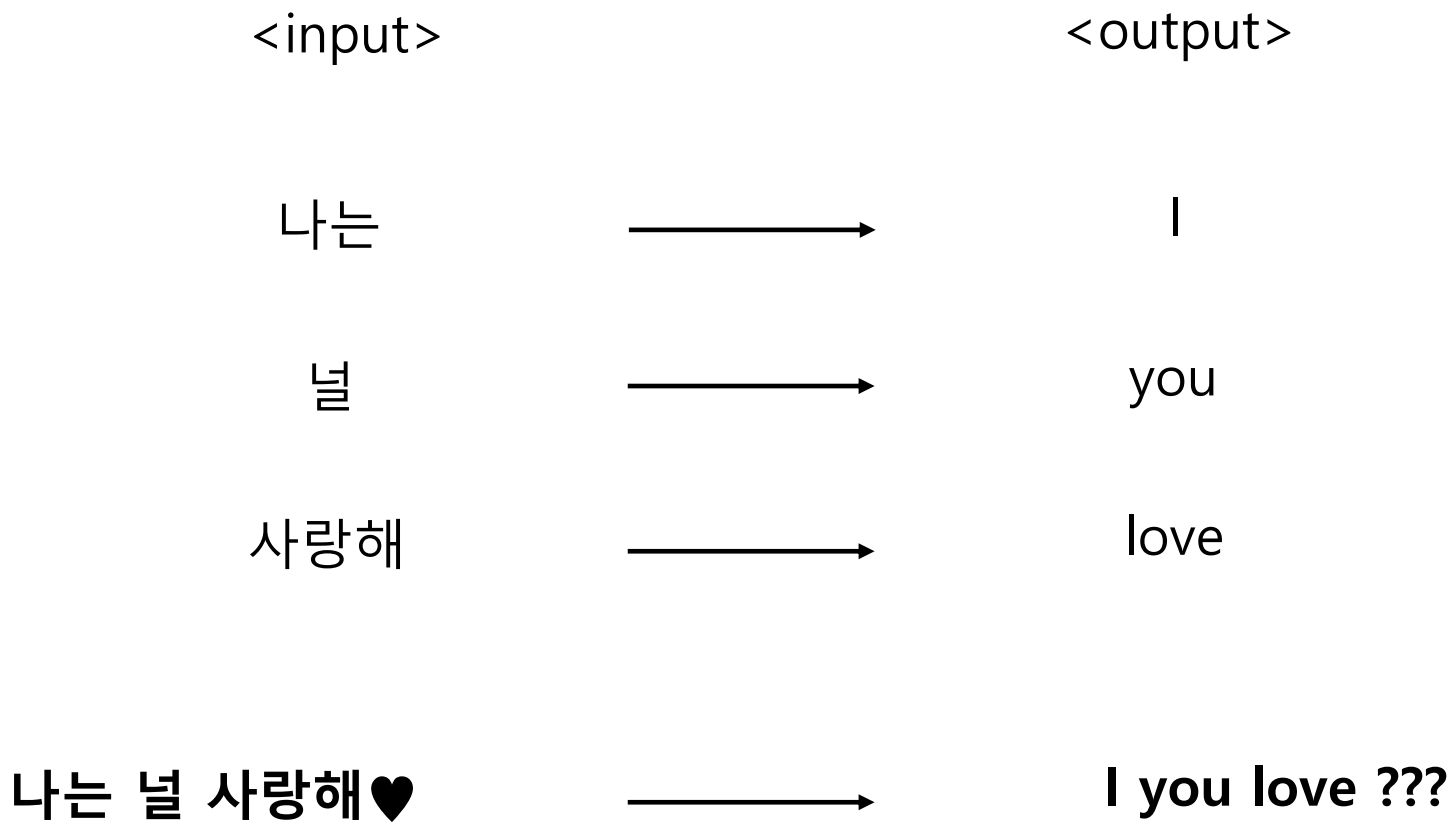
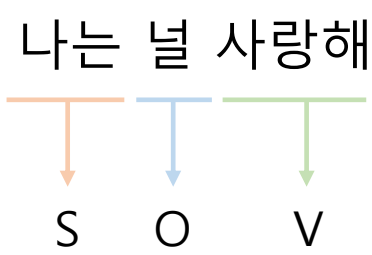


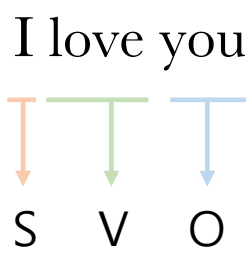
01. Translator

번역기를 만들어 보자 – 문제01

- 한국어, 일본어 : 주어 목적어 서술어 순으로 구성 (S-O-V)
- 영어, 중국어 : 주어 서술어 목적어로 구성 (S-V-O)

단어 별로 번역을 하면 **어순이 엇갈리는 문제**가 생긴다

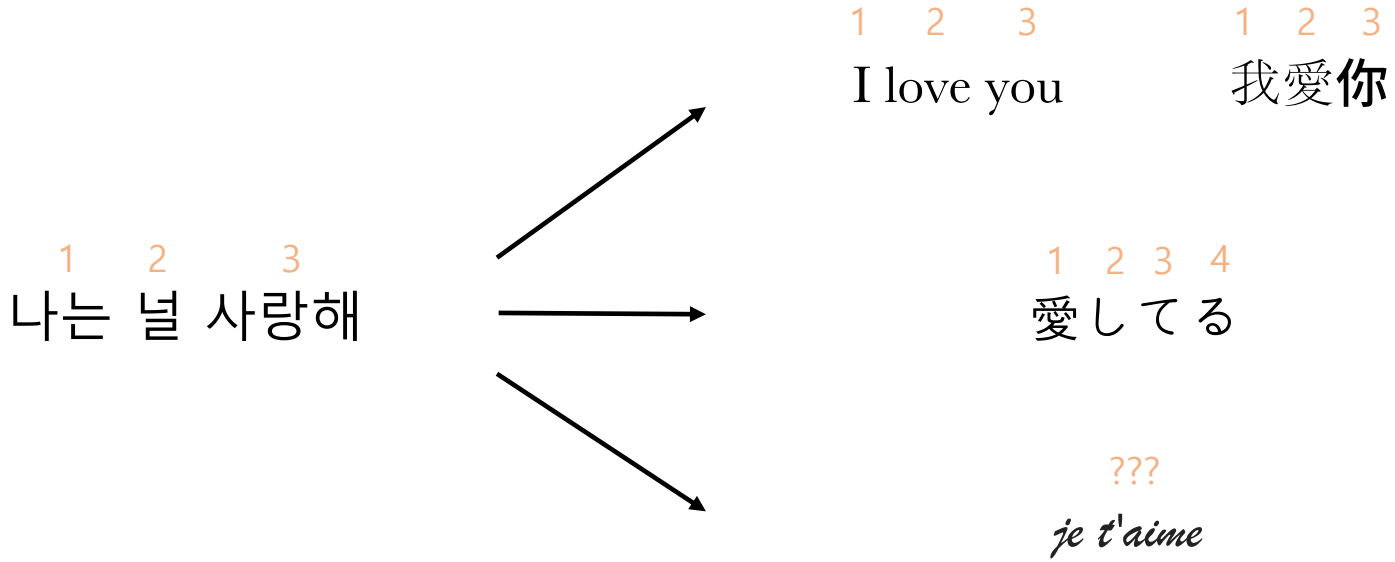




01. Translator

번역기를 만들어 보자 – 문제02

단어가 1:1로 수가 맞아 번역이 되는 경우가 이는 한편 **단어의 수가 바뀔 수도 있다**



02. seq2seq

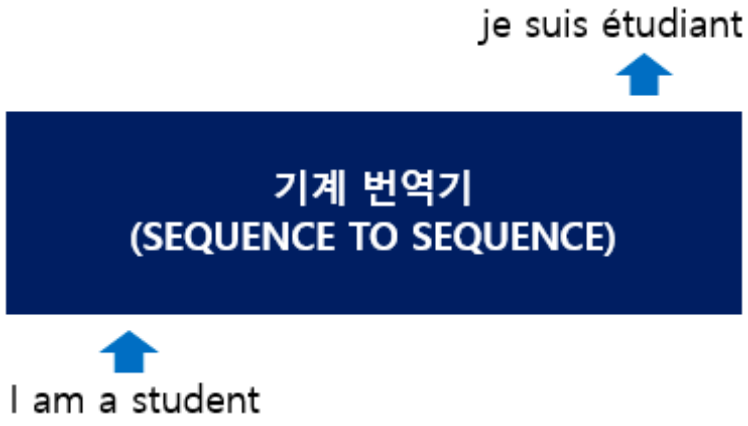
Sequence-to-sequence

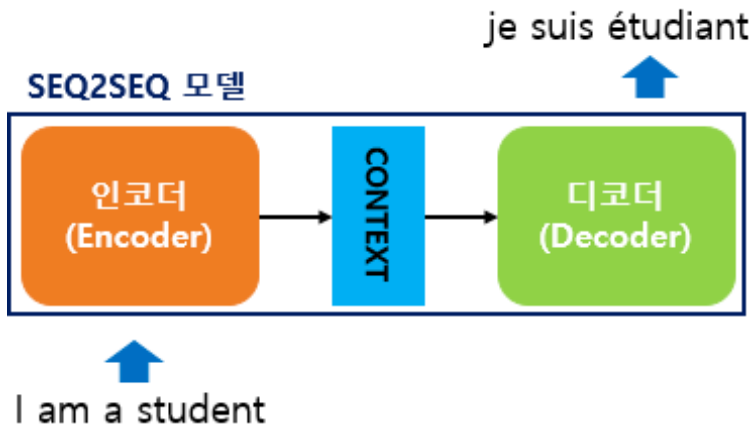
- 불어-영어 번역을 위해 2014년 처음 사용되었다
- **한 domain에서 다른 domain으로 시퀀스를 변환**하는 모델 학습

  ex) chatbot, machine translation, text summarization, STT, ...

  chatbot : 입력(질문), 출력(대답)

  machine translation : 입력(문장), 출력(번역 문장)

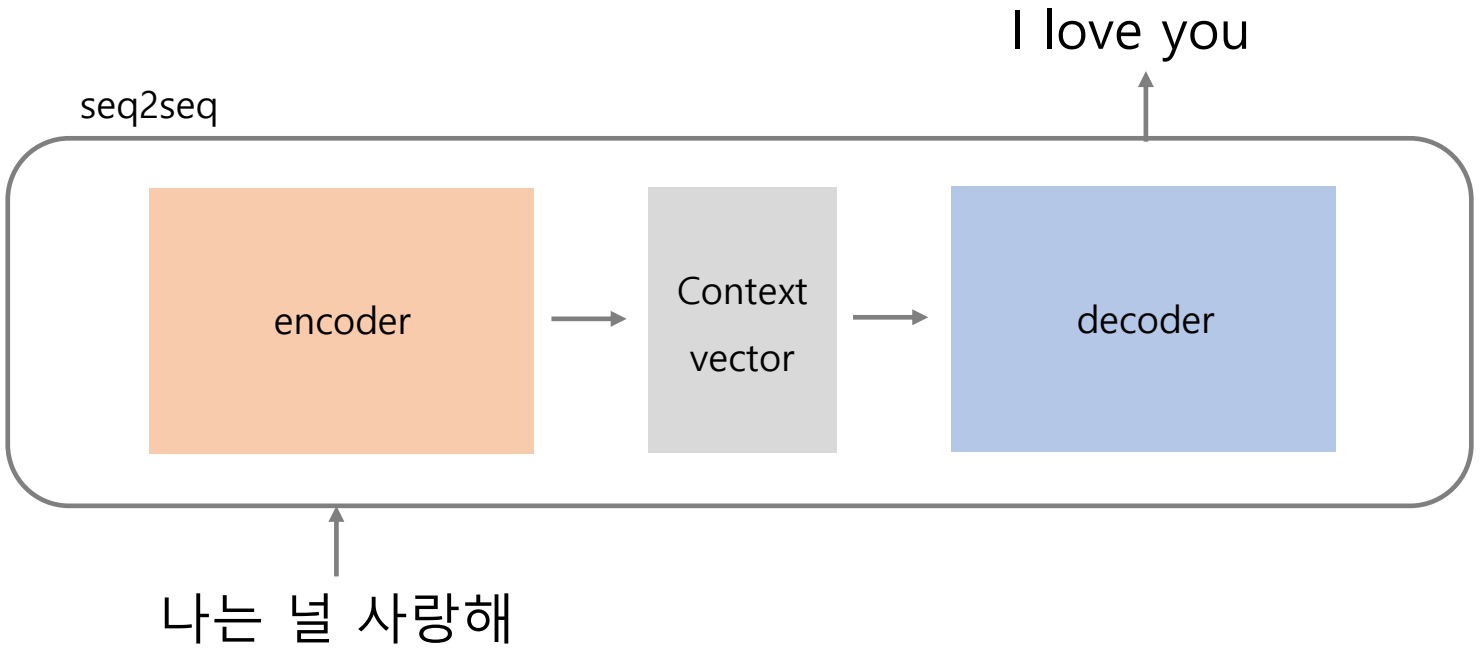




03. architecture

Seq2seq의 구조를 알아보자

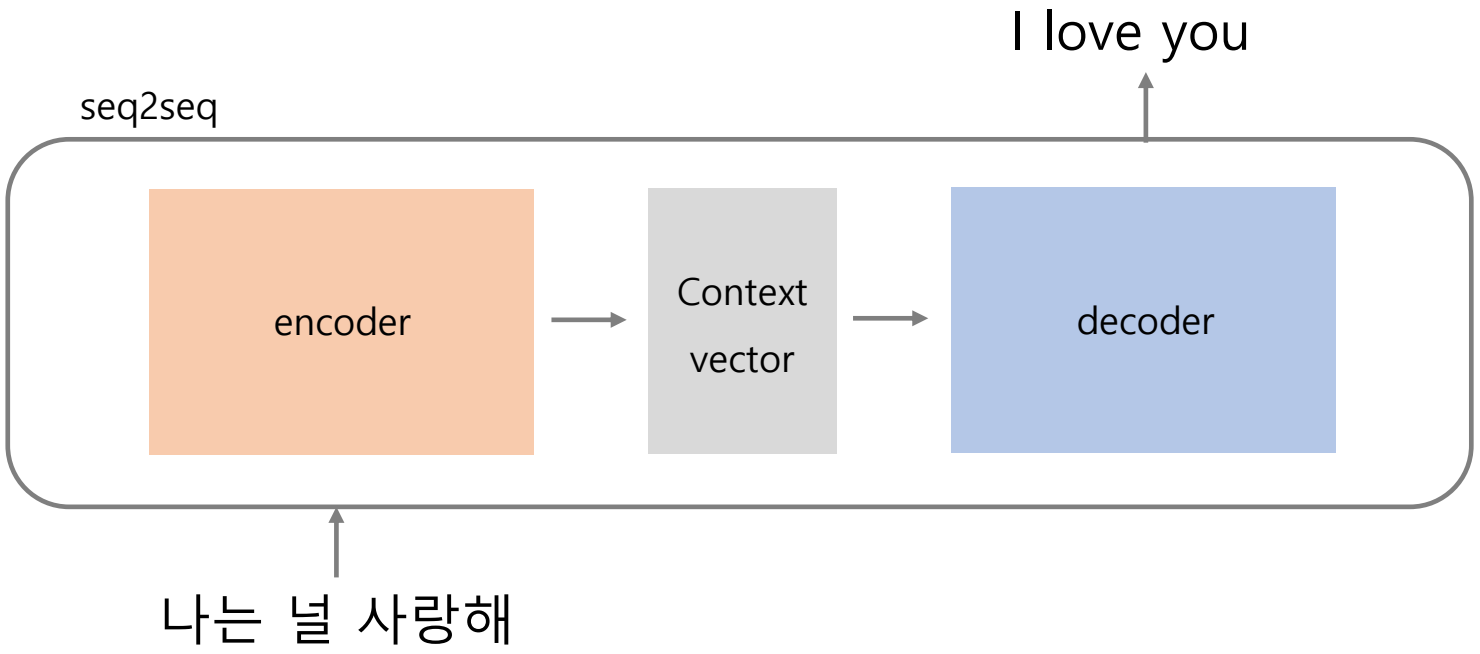
- **Encoder**
  - 입력 단어를 순차적으로 받음으로써 context vector 생성
  - 입력 문장의 정보가 하나의 context vector로 압축되면 decoder로 전송
- **Decoder**
  - context vector를 받아서 번역된 단어를 한 개씩 순차적으로 출력



03. architecture

Seq2seq의 구조를 알아보자

- **Context vector**
  - Encoder에서의 input에 대한 정보를 함축
- 입력 시퀀스, 출력 시퀀스의 단어 순서가 달라도 학습을 함으로써 **문법, 문맥 고려 가능**



03. architecture

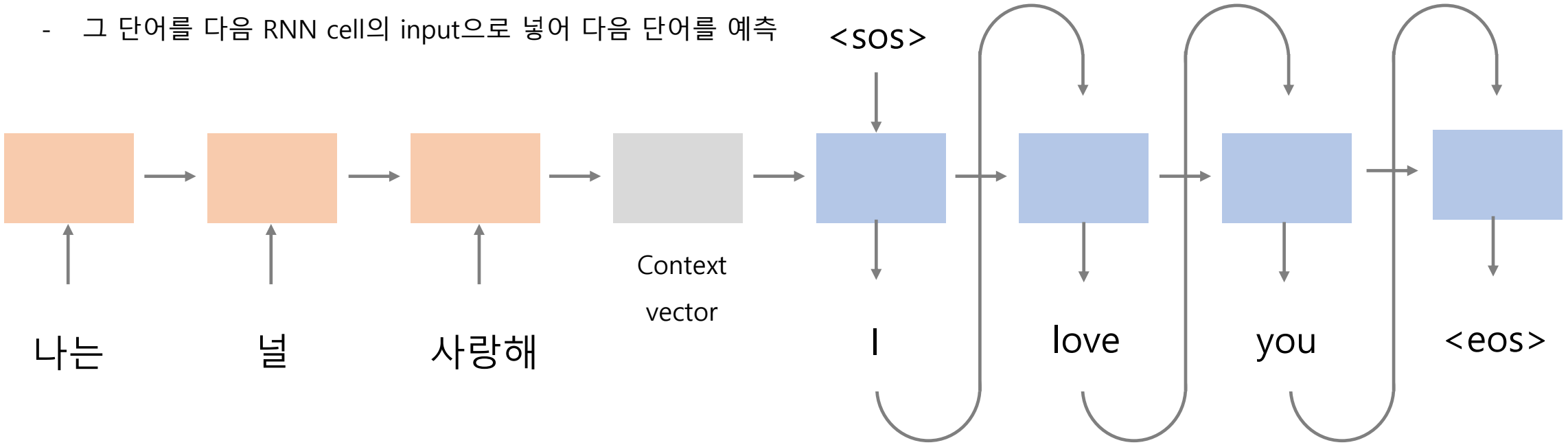
Seq2seq의 Train, test 때의 작동 방식

Train

- context vector, GT <sos> I love you 두 개를 받았을 때 I love you <eos>가 와야 한다고 정답을 알려주면서 학습

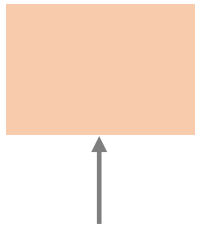
Test

- Decoder는 context vector, <sos>만을 input으로 받고 다음에 올 단어를 예측.
- 그 단어를 다음 RNN cell의 input으로 넣어 다음 단어를 예측



03. architecture

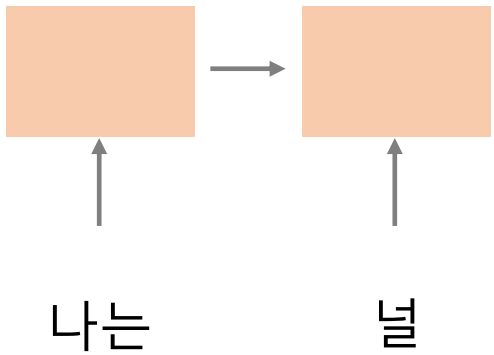
Seq2seq의



나는

03. architecture

Seq2seq의 구조를 알아보자



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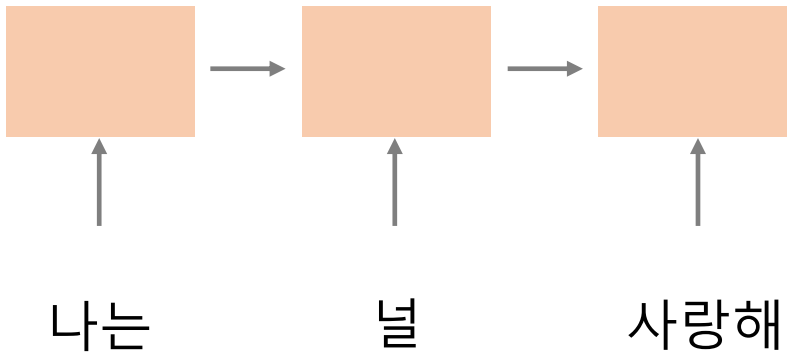

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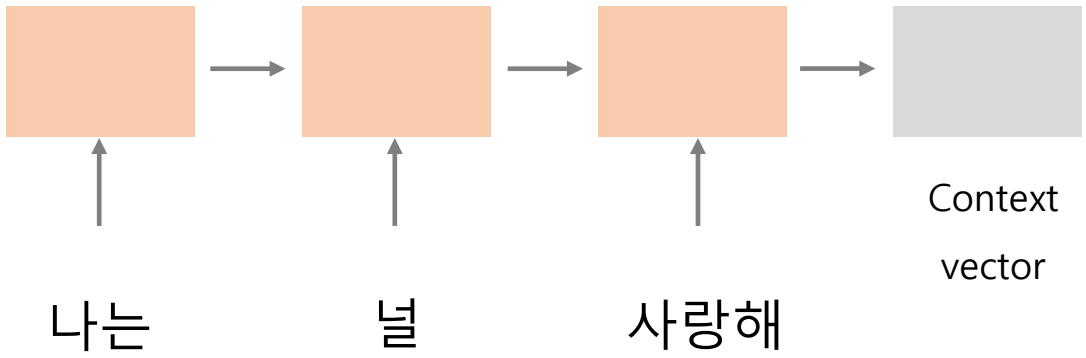

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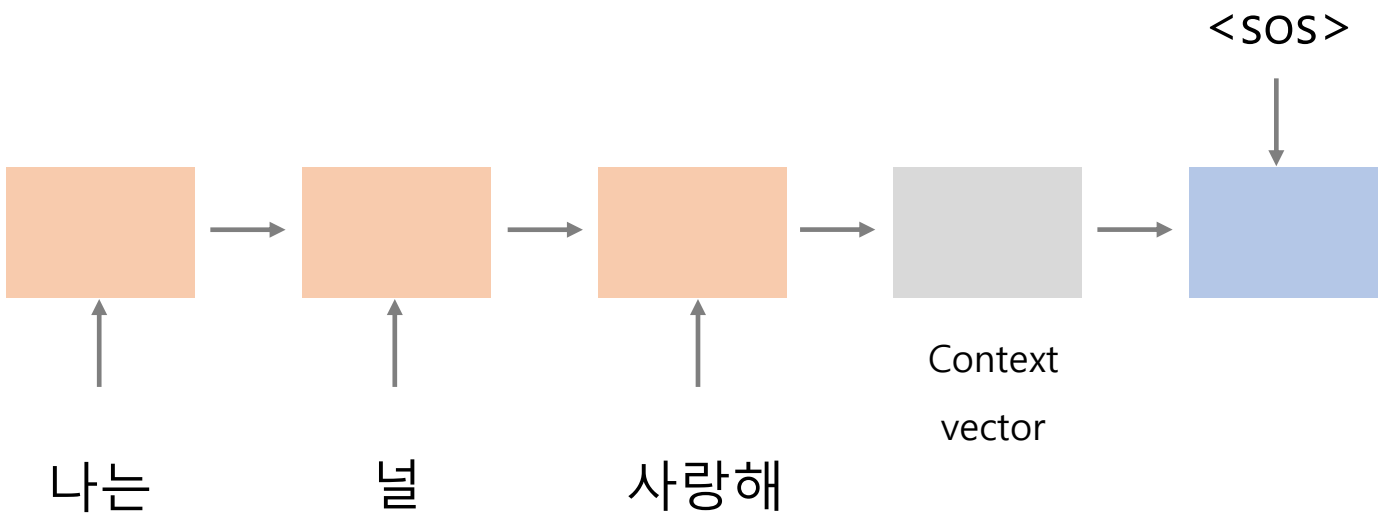

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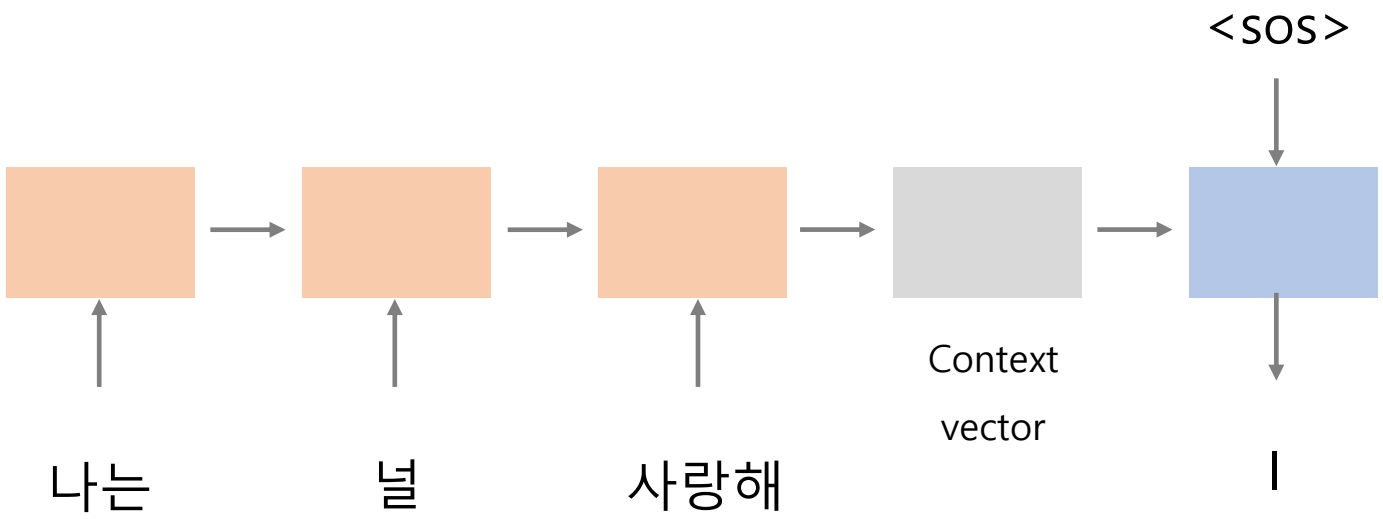

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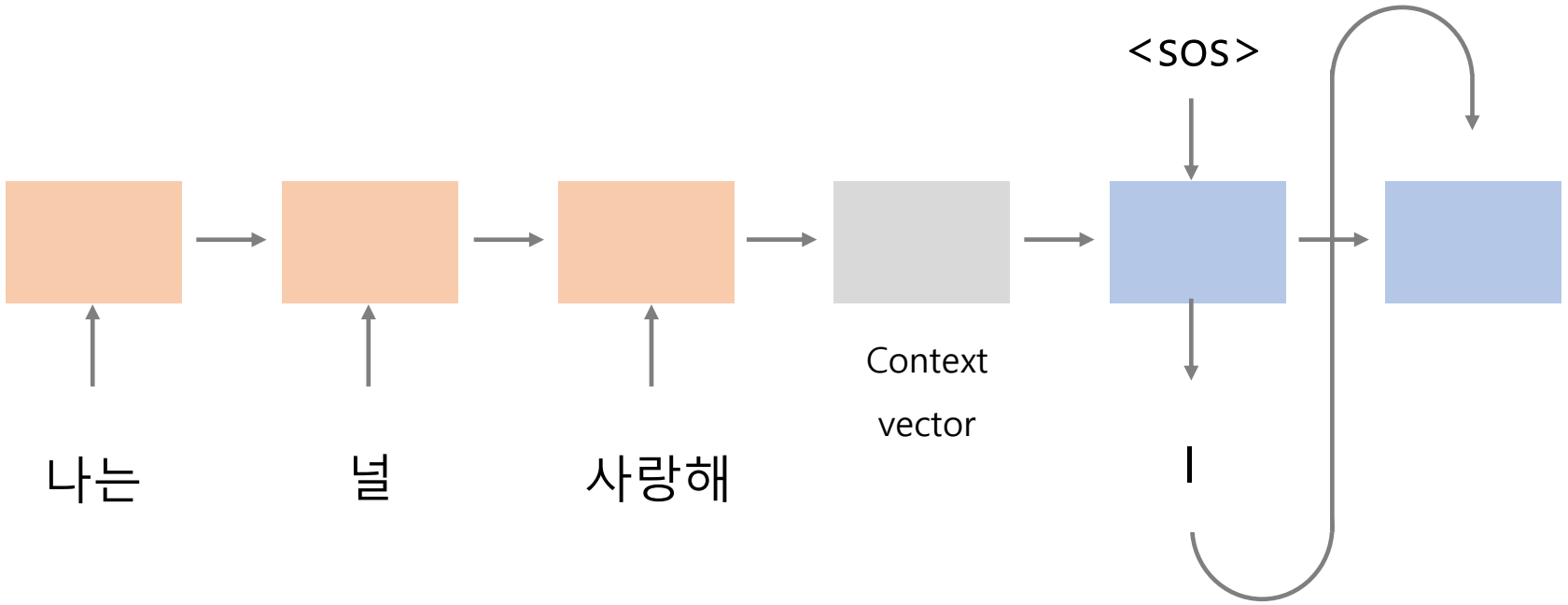

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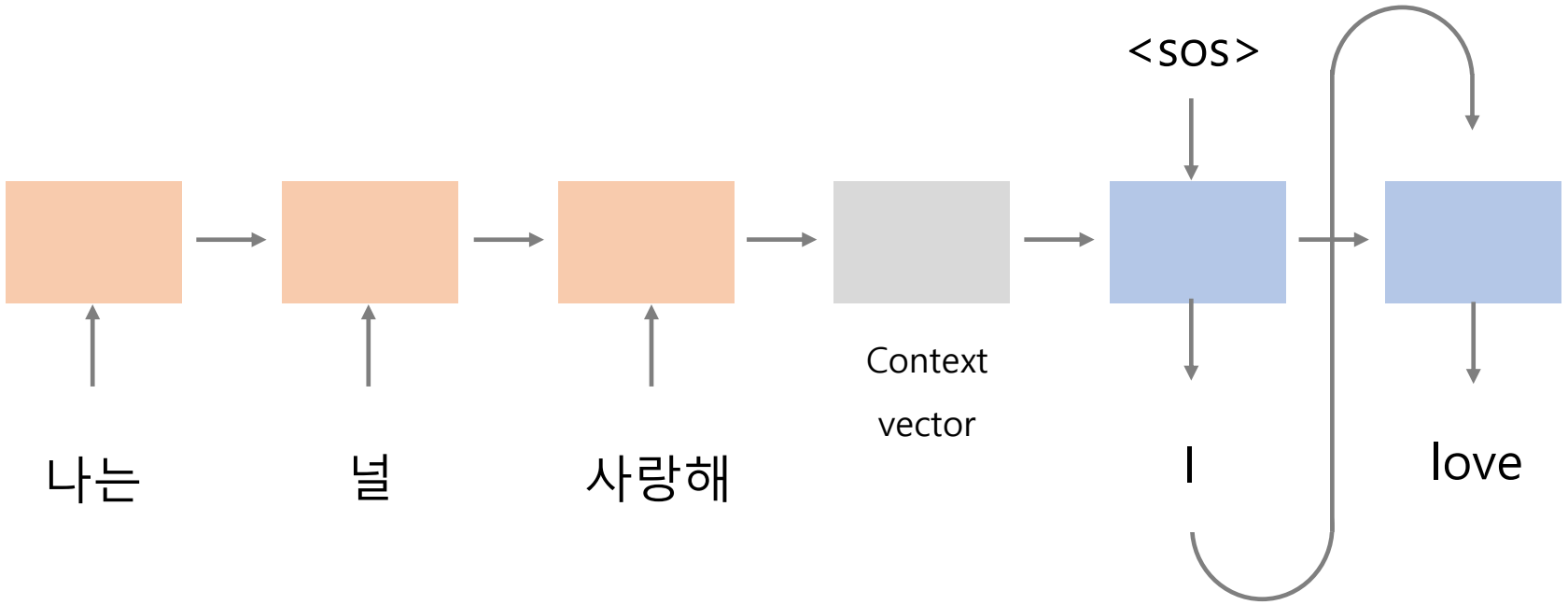

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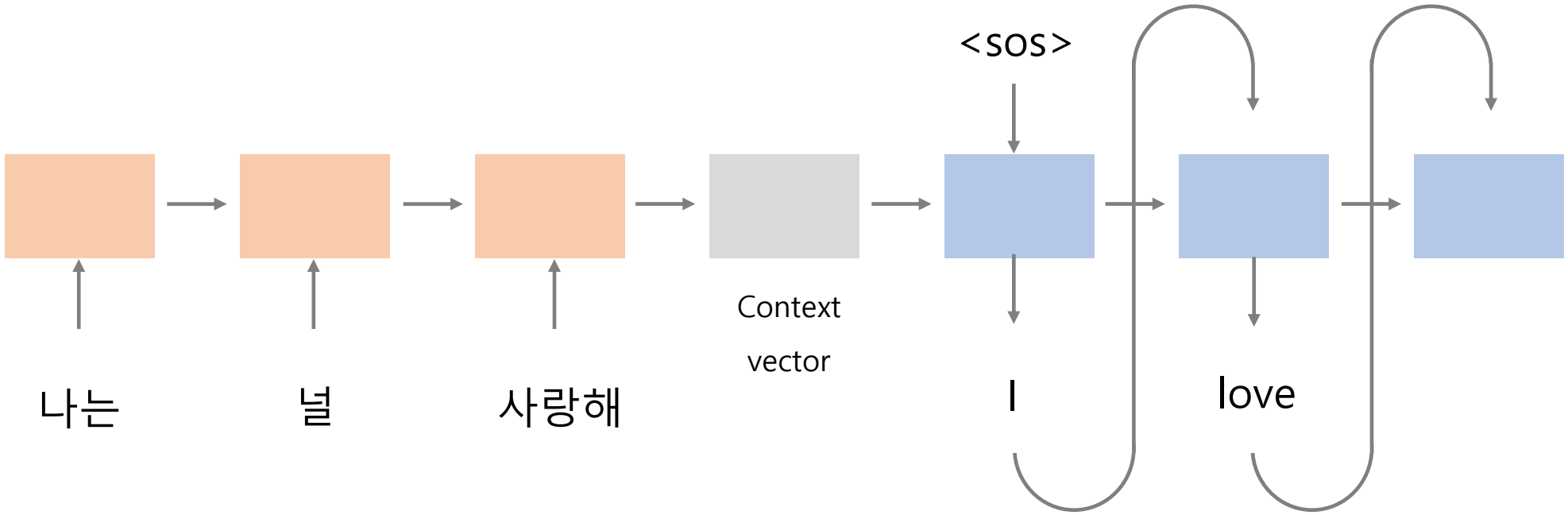

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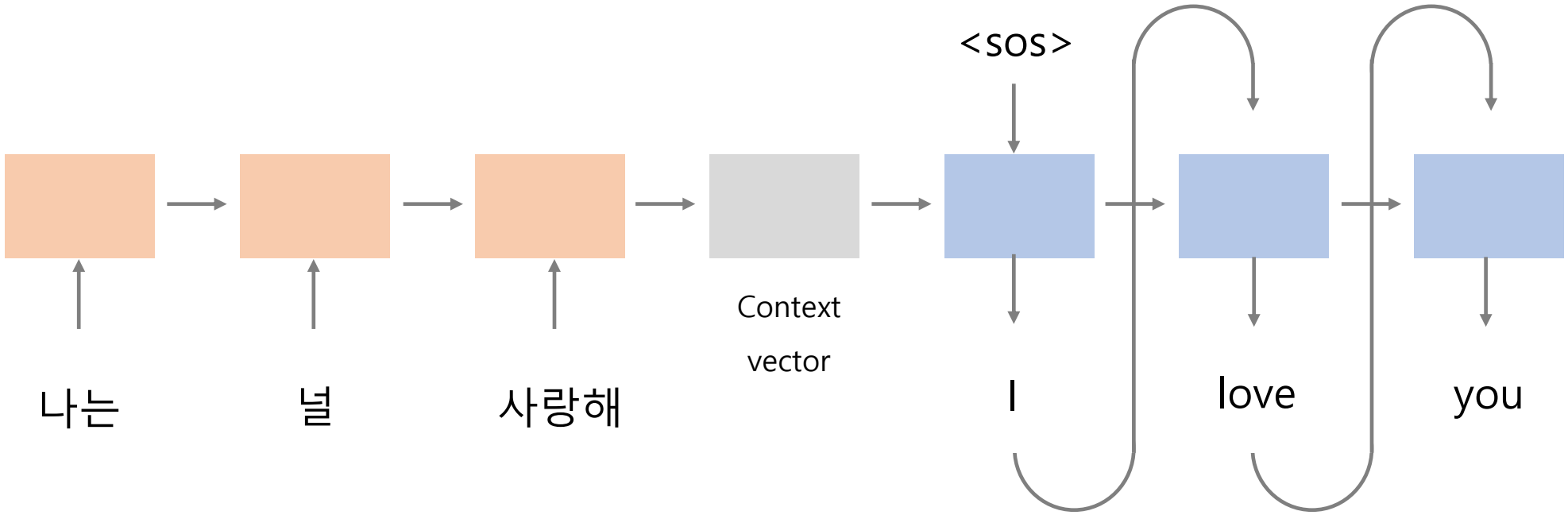

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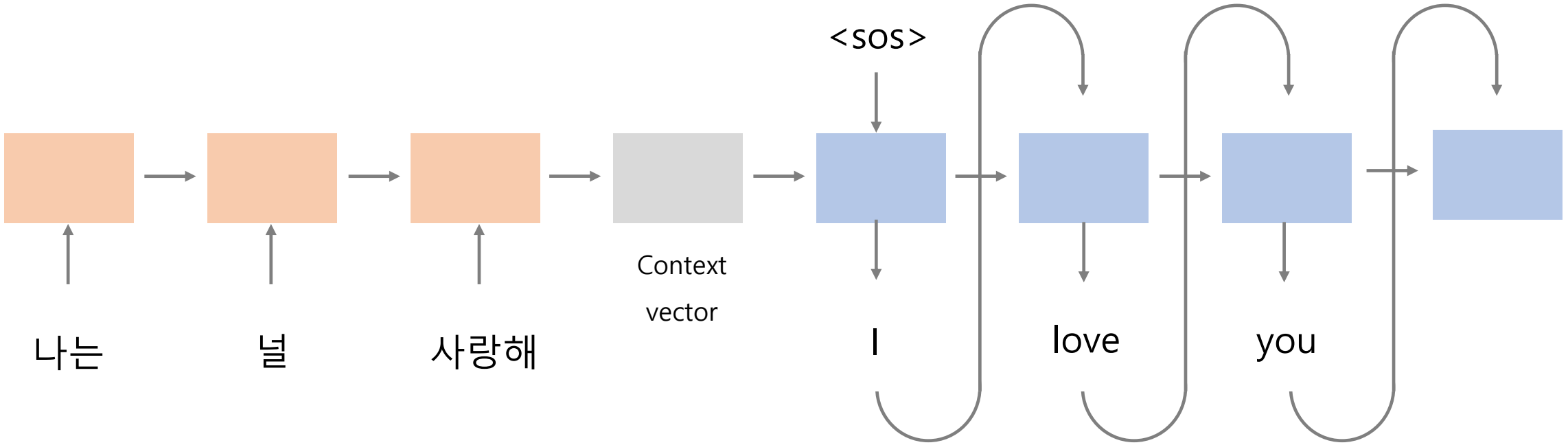

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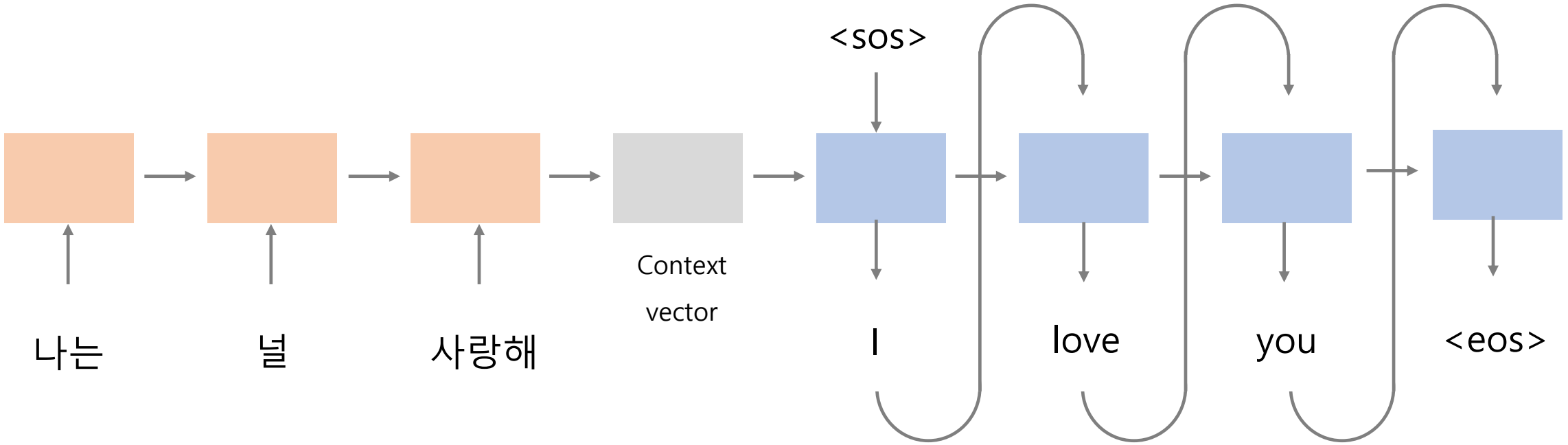
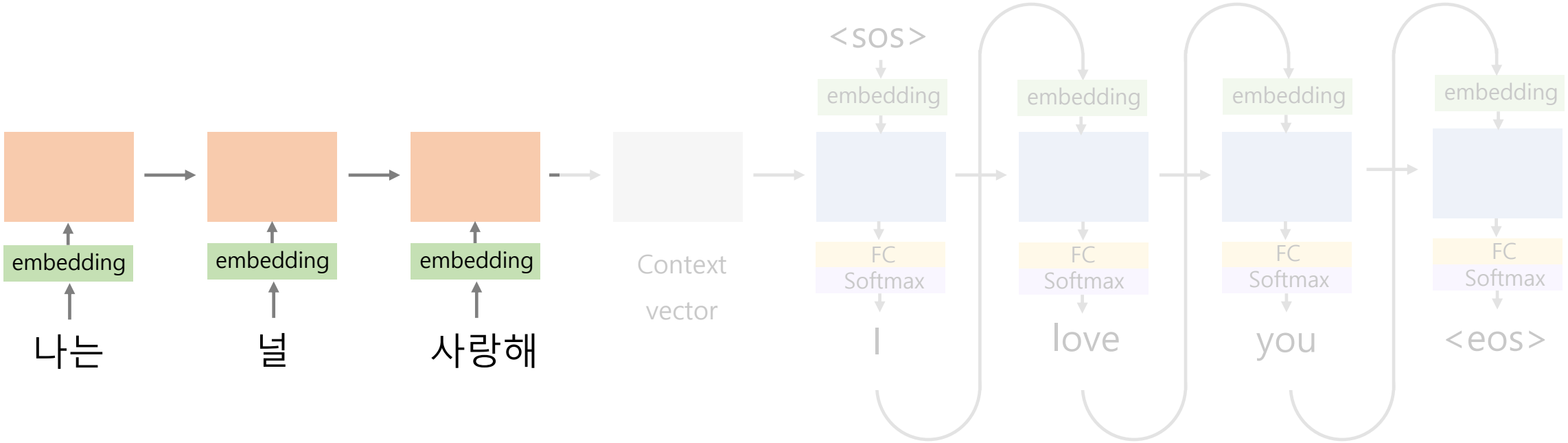


04. Layers

Seq2seq의 embedding, dense, softmax layers

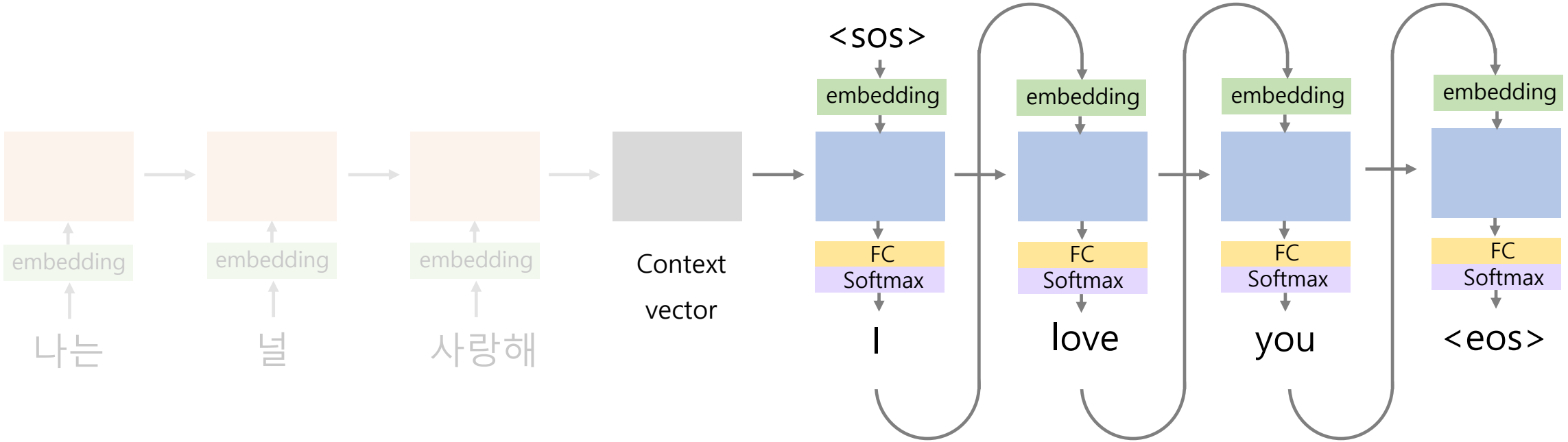
Seq2seq에서 사용되는 모든 단어들은 word embedding을 통해 **embedding vector**로 표현된다



04. Layers

Seq2seq의 embedding, fc, softmax layers

- RNN cell에서 어떠한 '단어'가 나올지 선택
- 각 시점에서 RNN cell으로부터 어떠한 output이 나오면 softmax를 통해 각 단어별 확률 값을 반환

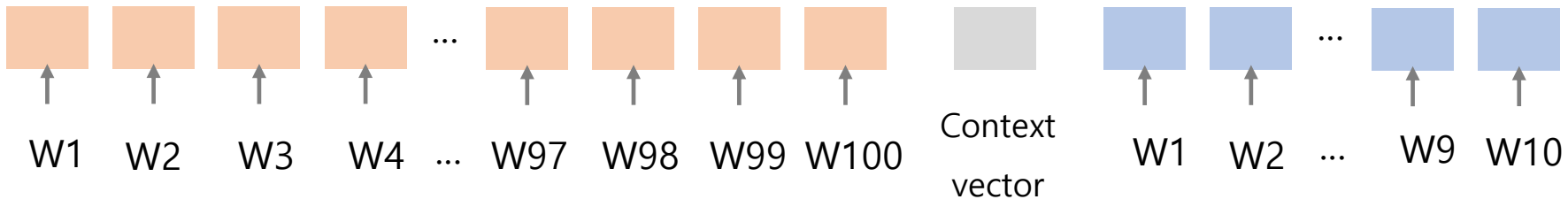


05. drawback

단순 seq2seq의 단점

Context vector의 사이즈는 input과 상관없이 고정

만약 문장이 길어질 경우 **context vector가 충분히 크지 않으면** 모든 내용을 함축할 만큼을 담을 수 없다

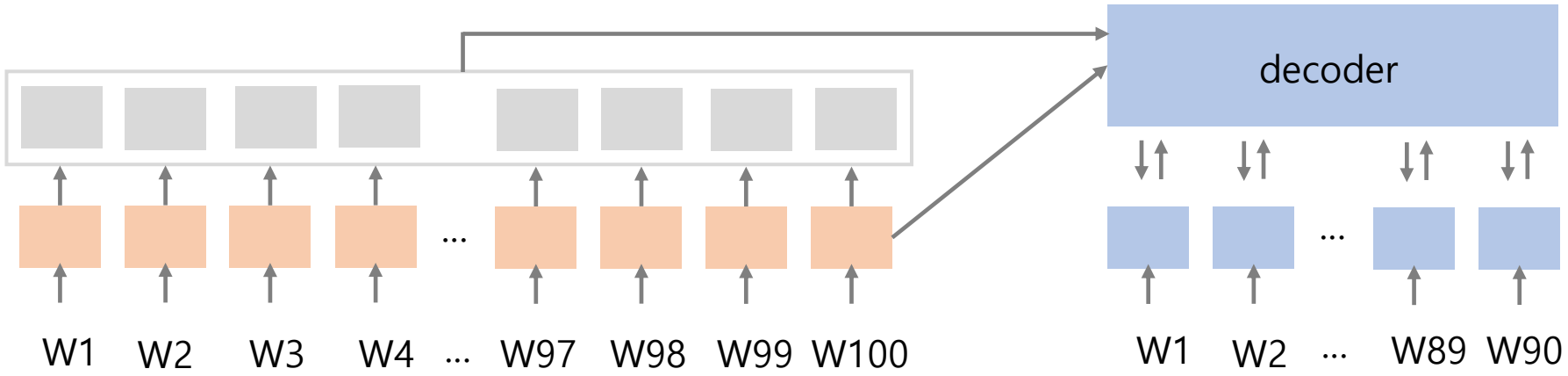


06. attention

Attention seq2seq

Attention 사용해 해결

- 기존엔 context vector만 사용 -> Encoder의 모든 state를 사용하면 context vector의 길이 제약에서 벗어날 수 있다
  - 각각의 state vector를 가지고 새로운 context vector 생성
  - encoder에 있었던 **모든 state 중에서 핵심 단어에만 집중하는 매커니즘**



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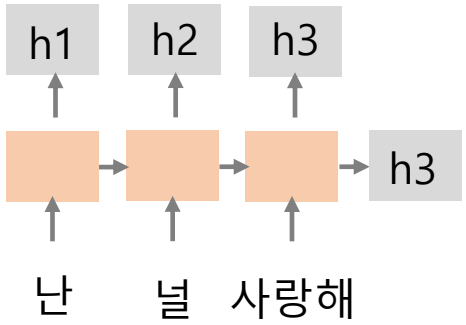

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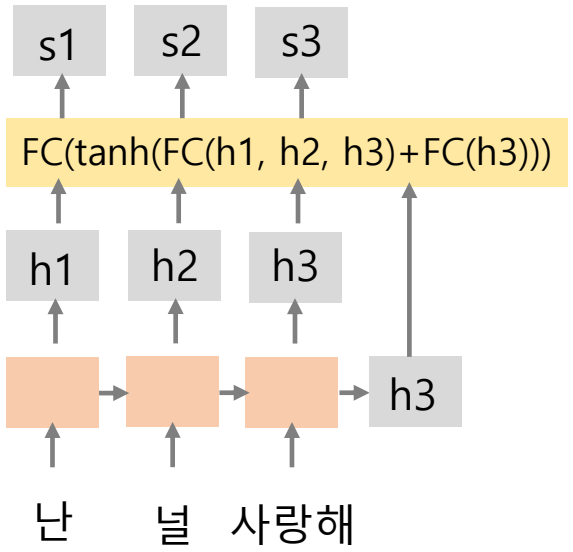

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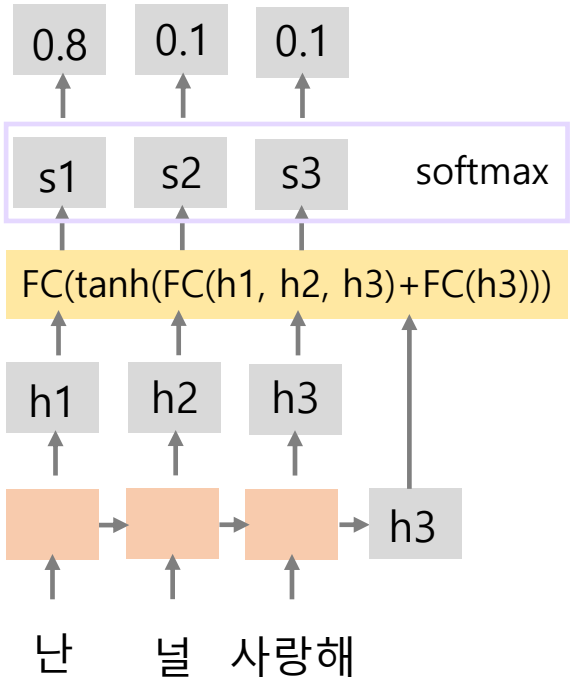

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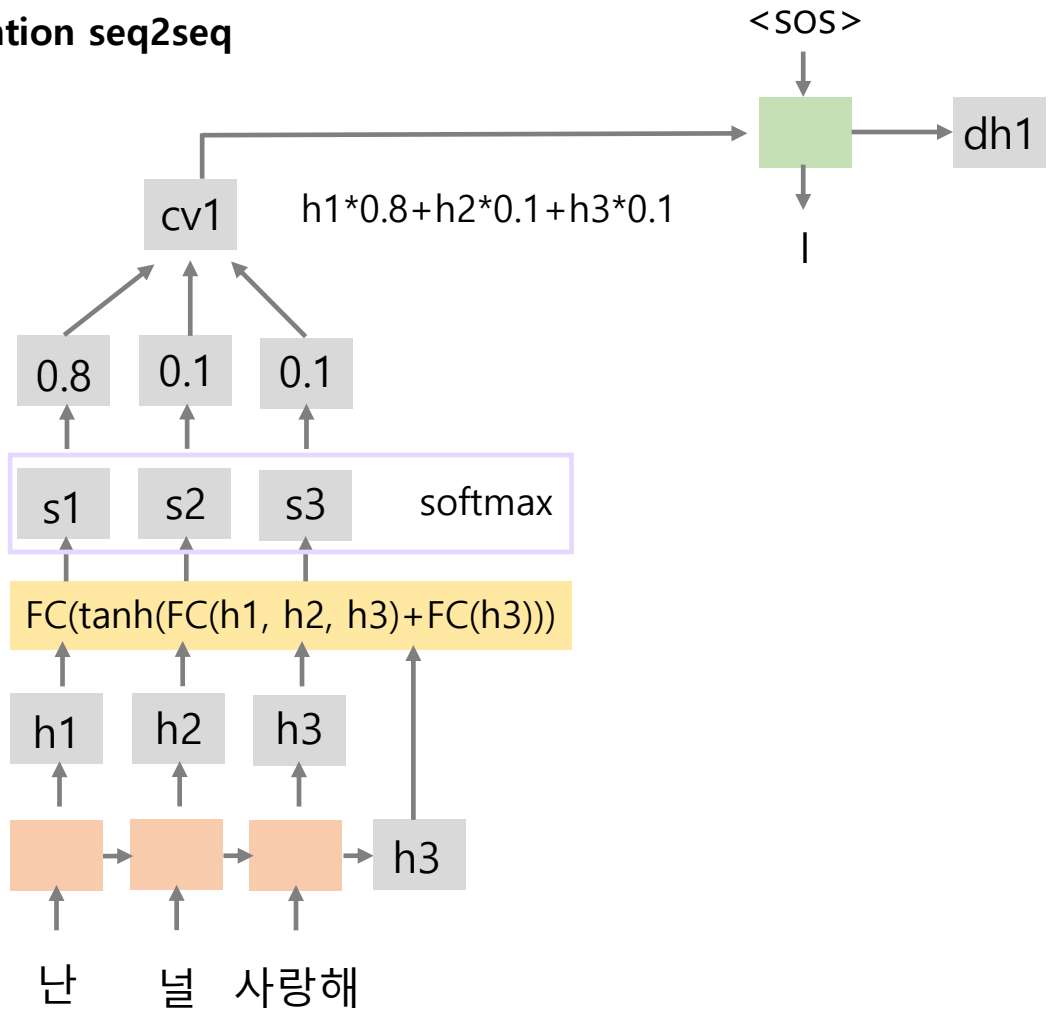

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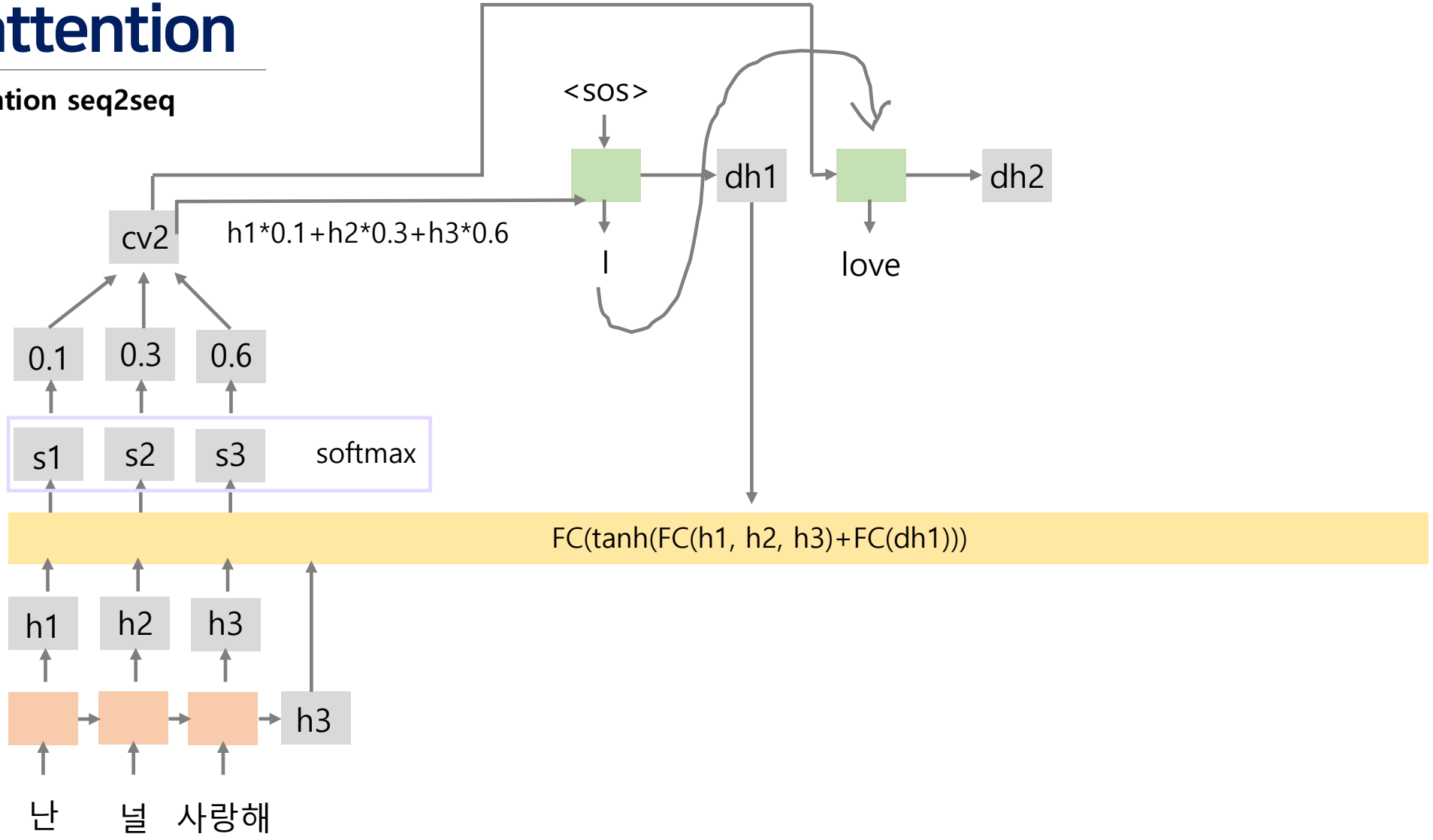

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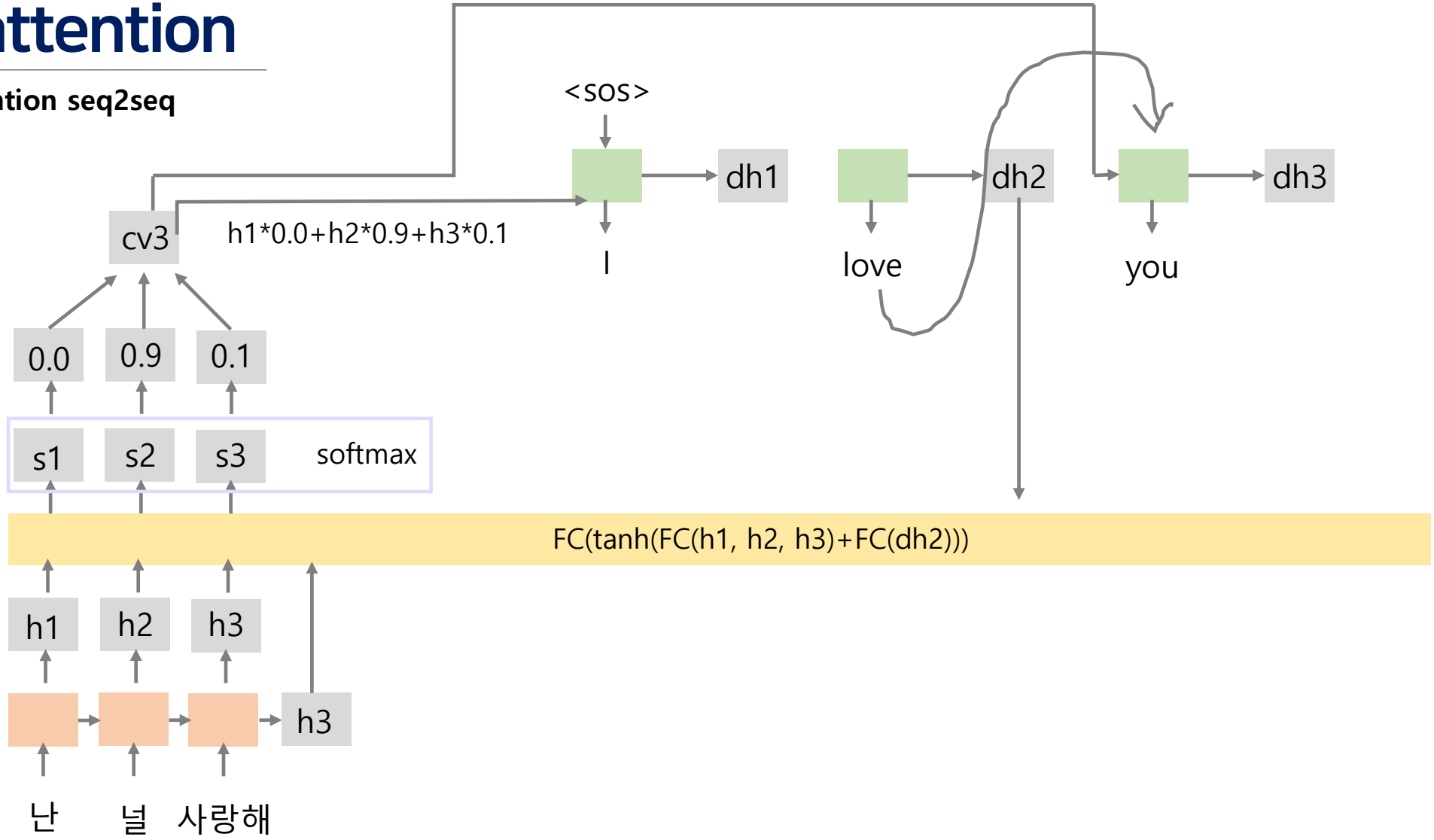

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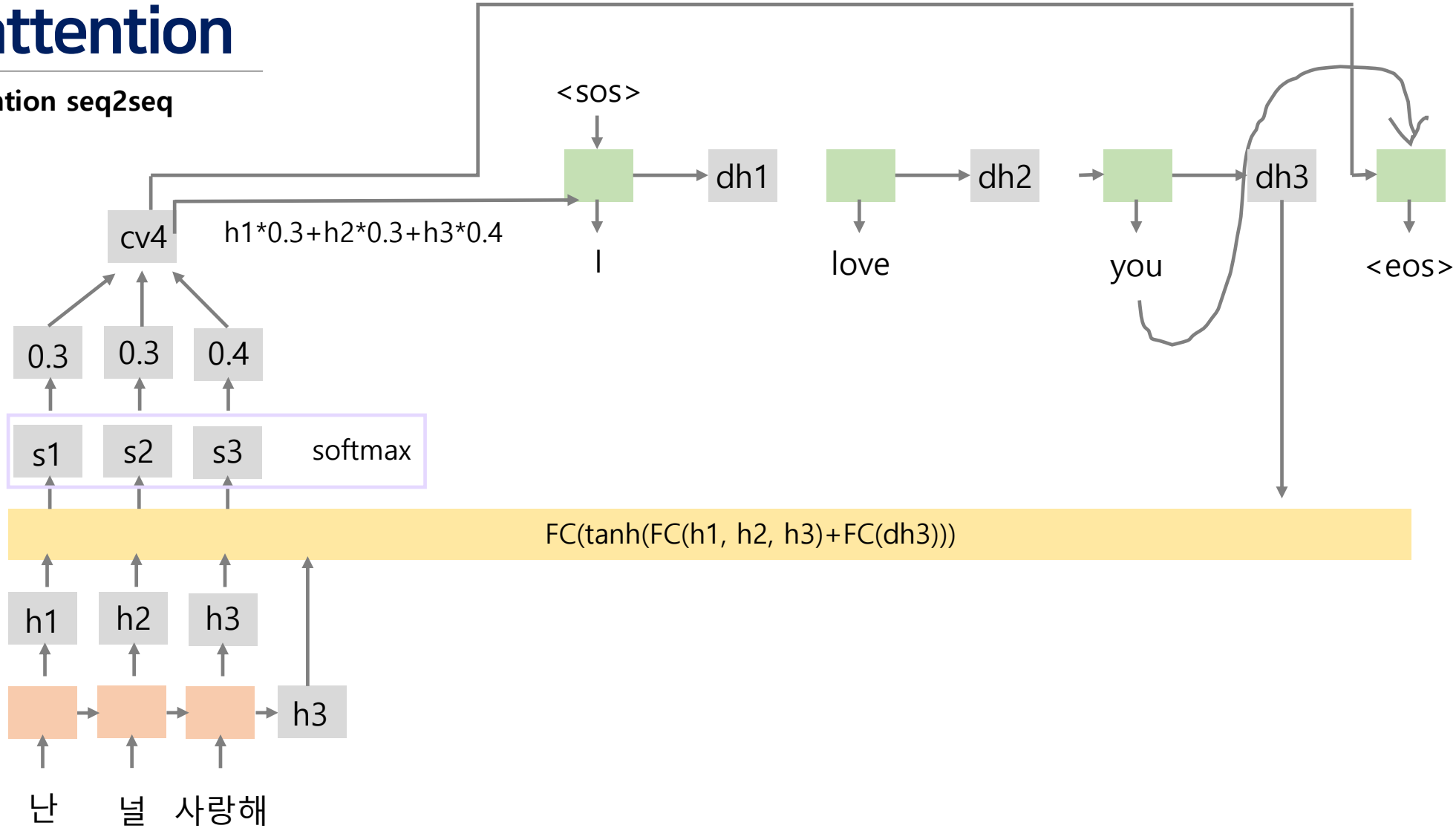

07. etc

구현 방법

- Context vector를 decoder의 초기 hidden state로만 사용
- Context vector를 decoder가 단어를 예측하는 매 시점마다 하나의 input으로 사용
- Attention mechanism을 통해 새로운 context vector를 구하여 매 시점마다 하나의 input으로 사용