14기 정규세션

ToBig's 14기 고경태

Machine Translation, Sequence-to-sequence and Attention

Contents

Overview

- Introduce a new task: Machine Translation

is a major use-case of

- Introduce a new neural architecture: sequence-to-sequence

is improved by

- Introduce a new neural technique: attention

Machine Translation -> sequence to sequence -> attention!

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Machine Translation

Machine Translation

x: *L'homme est né libre, et partout il est dans les fers*

y: *Man is born free, but everywhere he is in chains*

MT는 한 (소스) 언어의 문장을 (목표) 언어의 문장으로 번역하는 것.

1950`s : Early Machine Translation

Machine Translation research began in the early 1950s.

- Russian → English (motivated by the Cold War!)

1990s-2010s: Statistical Machine Translation

$$= \text{argmax}_y \underbrace{P(x|y)}\underbrace{P(y)}$$

Translation Model

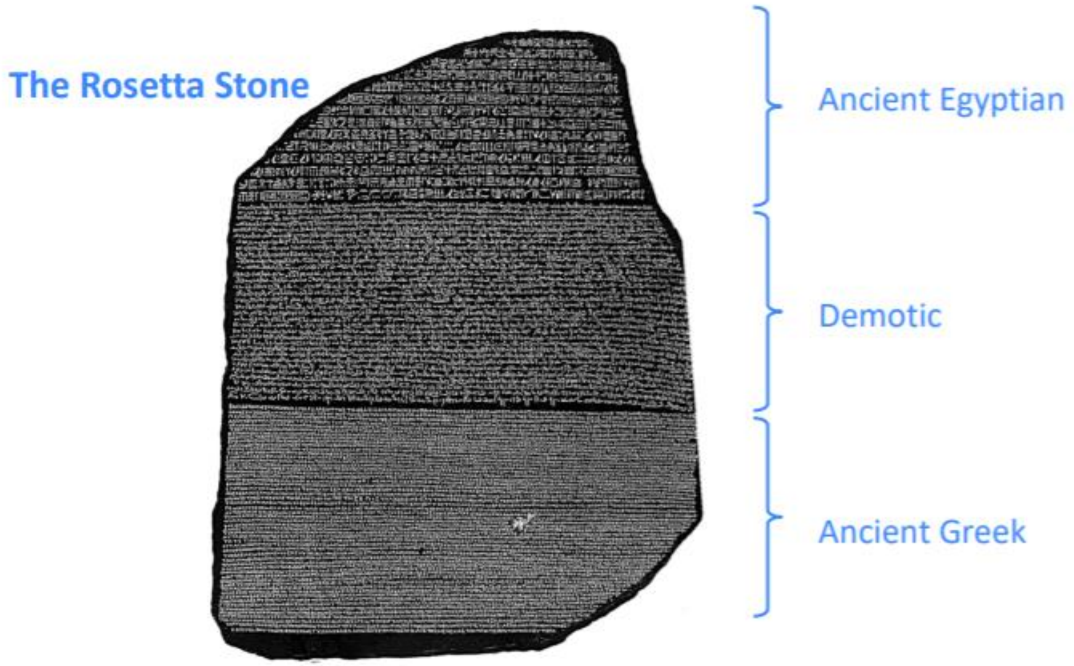
Models how words and phrases should be translated (*fidelity*). Learnt from parallel data.

Language Model

Models how to write good English (*fluency*). Learnt from monolingual data.

1. Translation Model : 작은 단어와 구의 번역
2. Language Model : 좋은 문장, 좋은 구조 도출

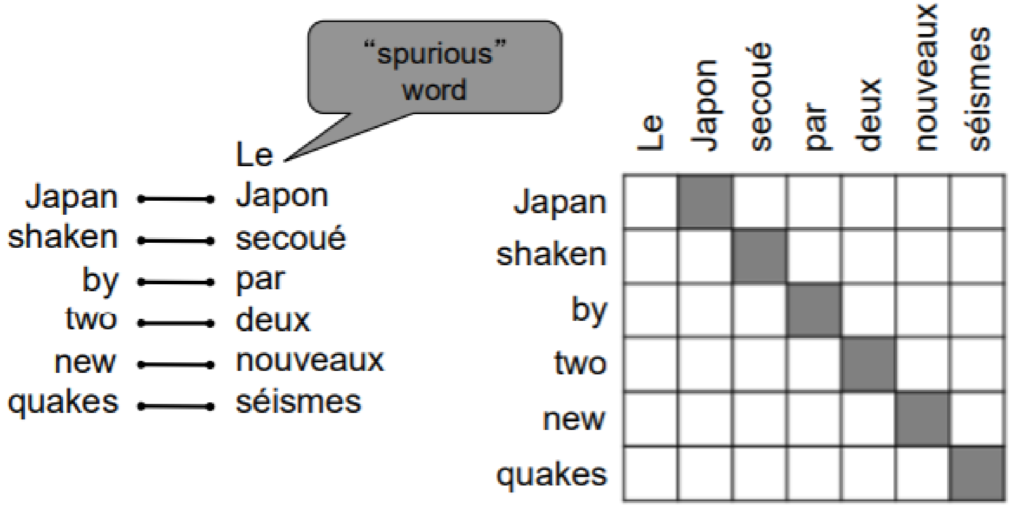
Learning alignment for SMT



$$P(x, a|y)$$

A is the alignment

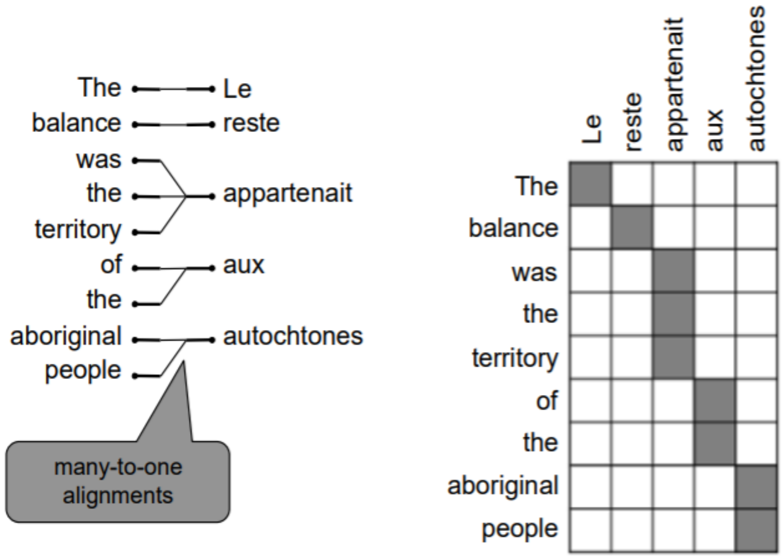
What is alignment?



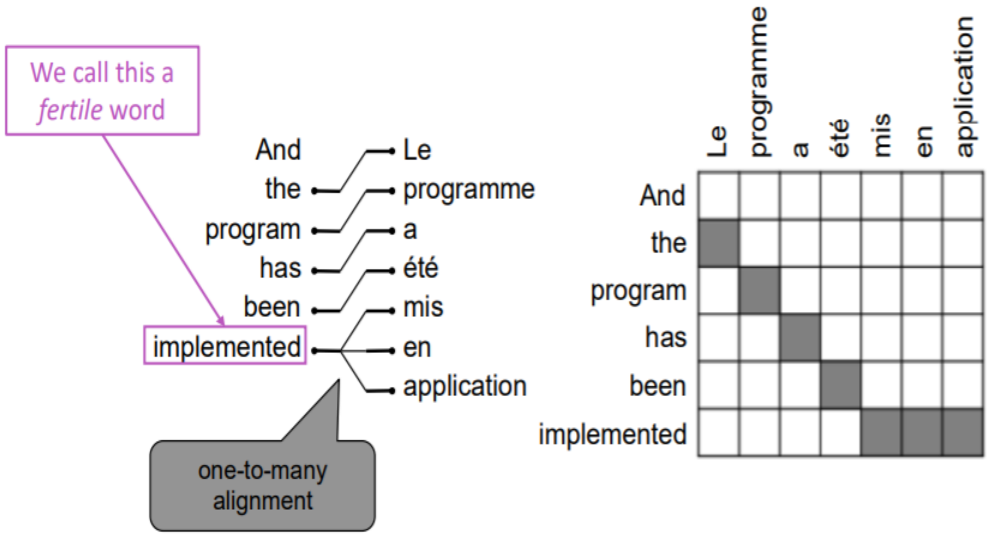
1. 정렬이란, 두 문장 사이에서 특정 단어쌍들의 대응
2.. 어떤 단어들은 대응되지 않을 수도..

Alignment is complex

Alignment can be many-to-one

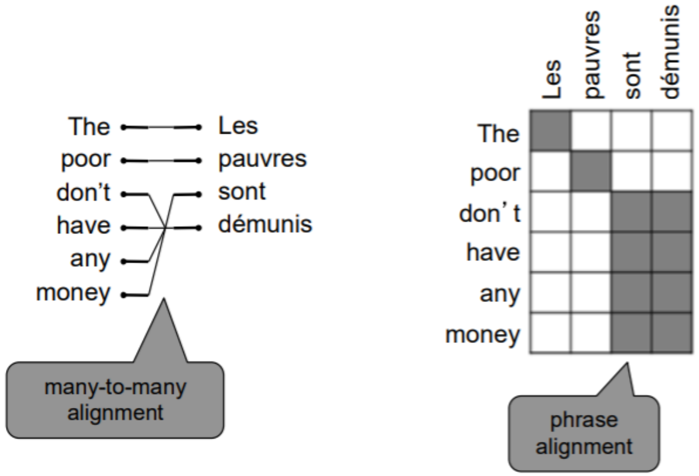


Alignment can be one-to-many



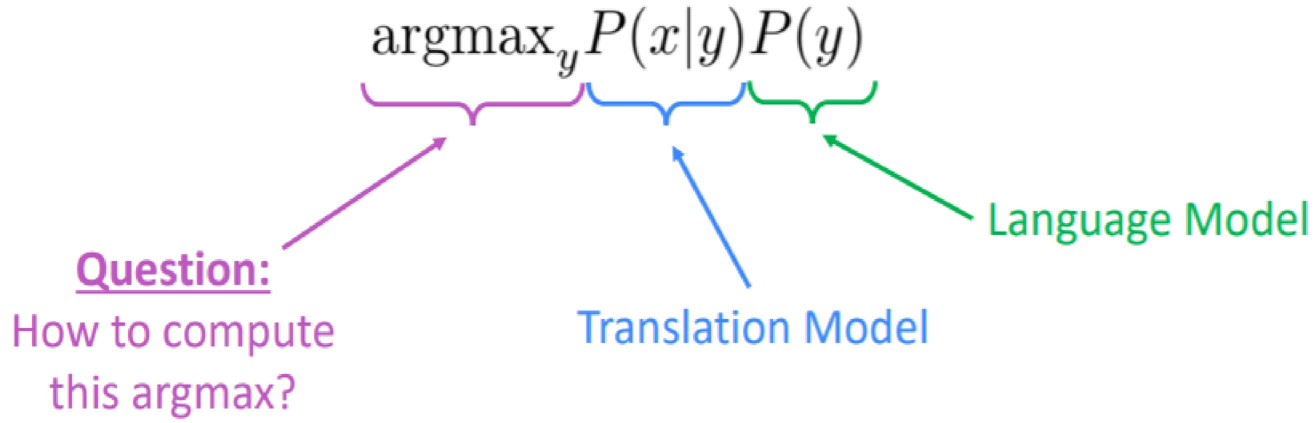
Alignment is complex, how learn?

Alignment can be many-to-many (phrase-level)



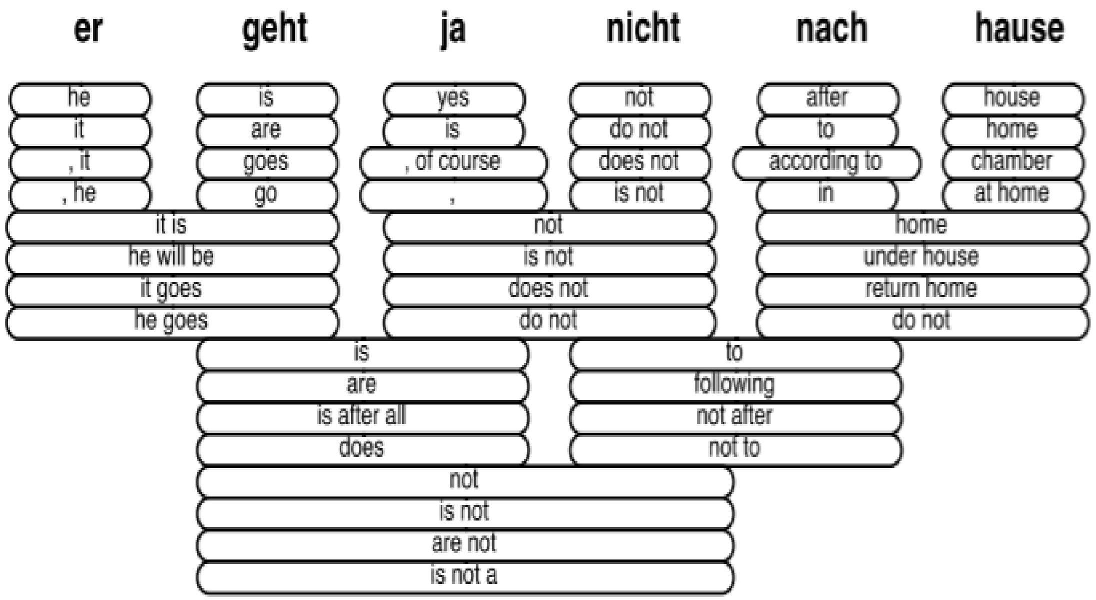
How learning?

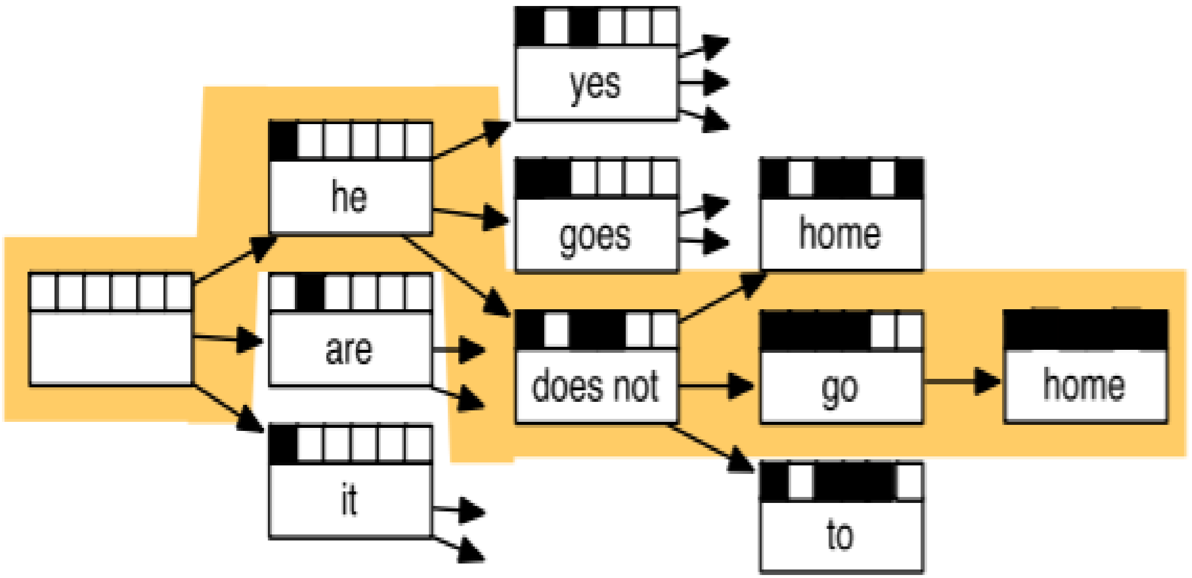
Decoding for SMT



1. 무차별 대입 솔루션
2. Heuristic 알고리즘

Decoding for SMT





1990s-2010s: Statistical Machine Translation

$$= \text{argmax}_y \underbrace{P(x|y)}_{\text{Translation Model}} \underbrace{P(y)}_{\text{Language Model}}$$

Translation Model

Models how words and phrases should be translated (*fidelity*).
Learnt from parallel data.

Language Model

Models how to write good English (*fluency*).
Learnt from monolingual data.

1. 좋은 성능을 내지만 매우 복잡한 구조
2. 각 system은 각 부분으로 나눠서 sub-system들이 모여 있는 형태
3. 많은 feature engineering이 필요
4. 추가적인 많은 자료 필요
5. 사람의 손을 많이 거쳐야함

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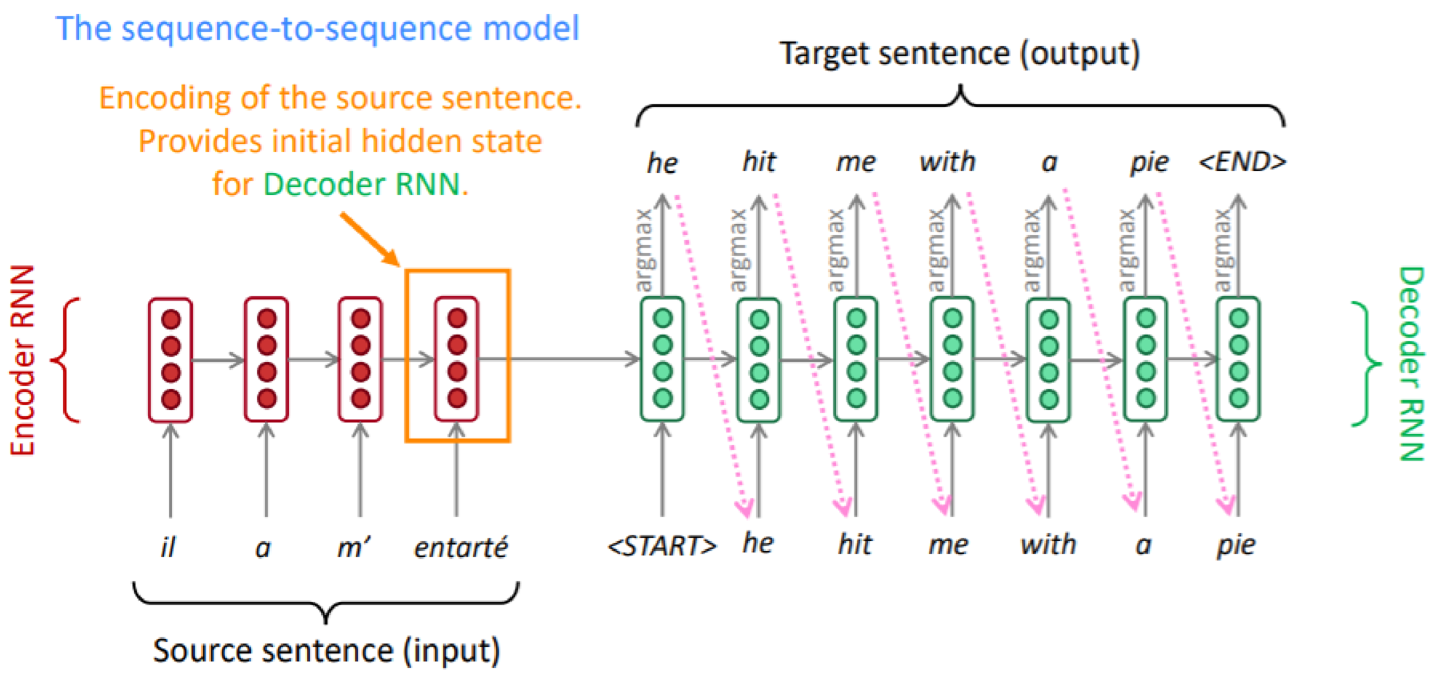
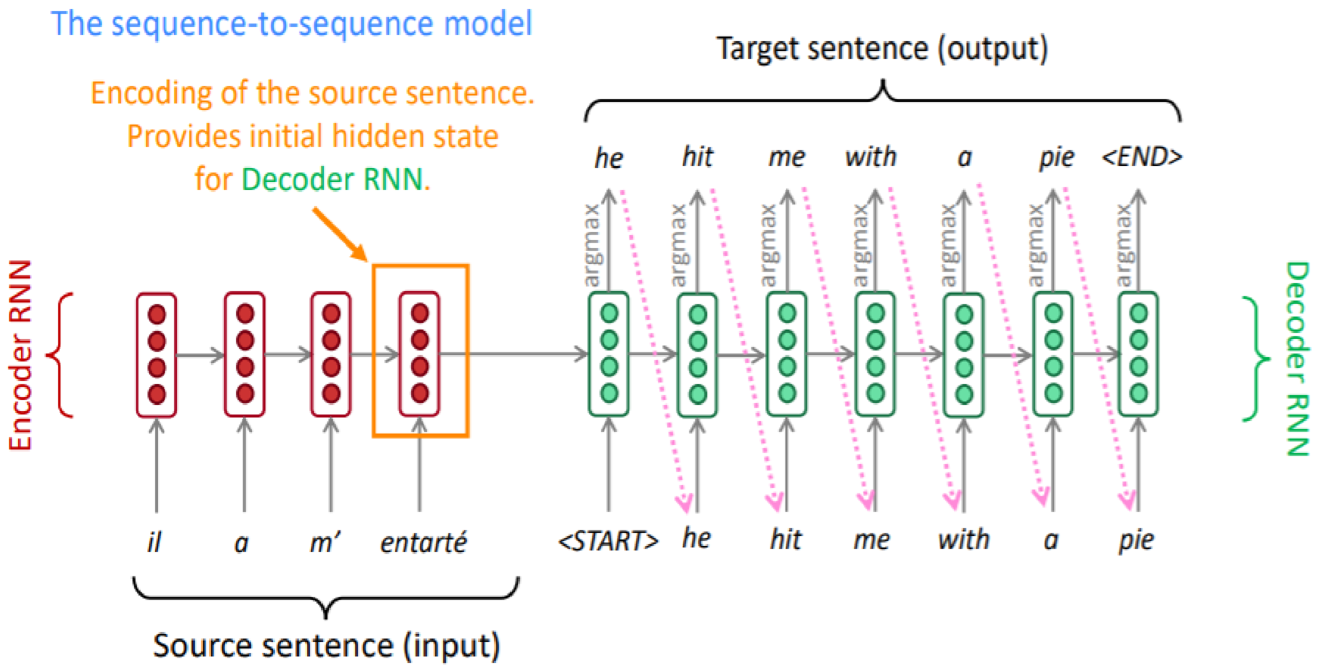
Neural Machine Translation
(Sequence to Sequence)

Neural Machine Translation (NMT)



1. 단일 신경망으로 기계번역을 하는 방법
2. 두개의 RNN을 포함한 seq-to-seq
3. 언어모델인 Decoder RNN은 target sentence를 생성
4. Output이 다음 단계의 input이 됨.

Sequence-to-sequence is versatile!



1. Summariztion (long text -> short text)
2. Dialogue (previous utterances -> next utterance)
3. Parsing (input text -> output parse as sequence)
4. Code generation (natural language -> python code)

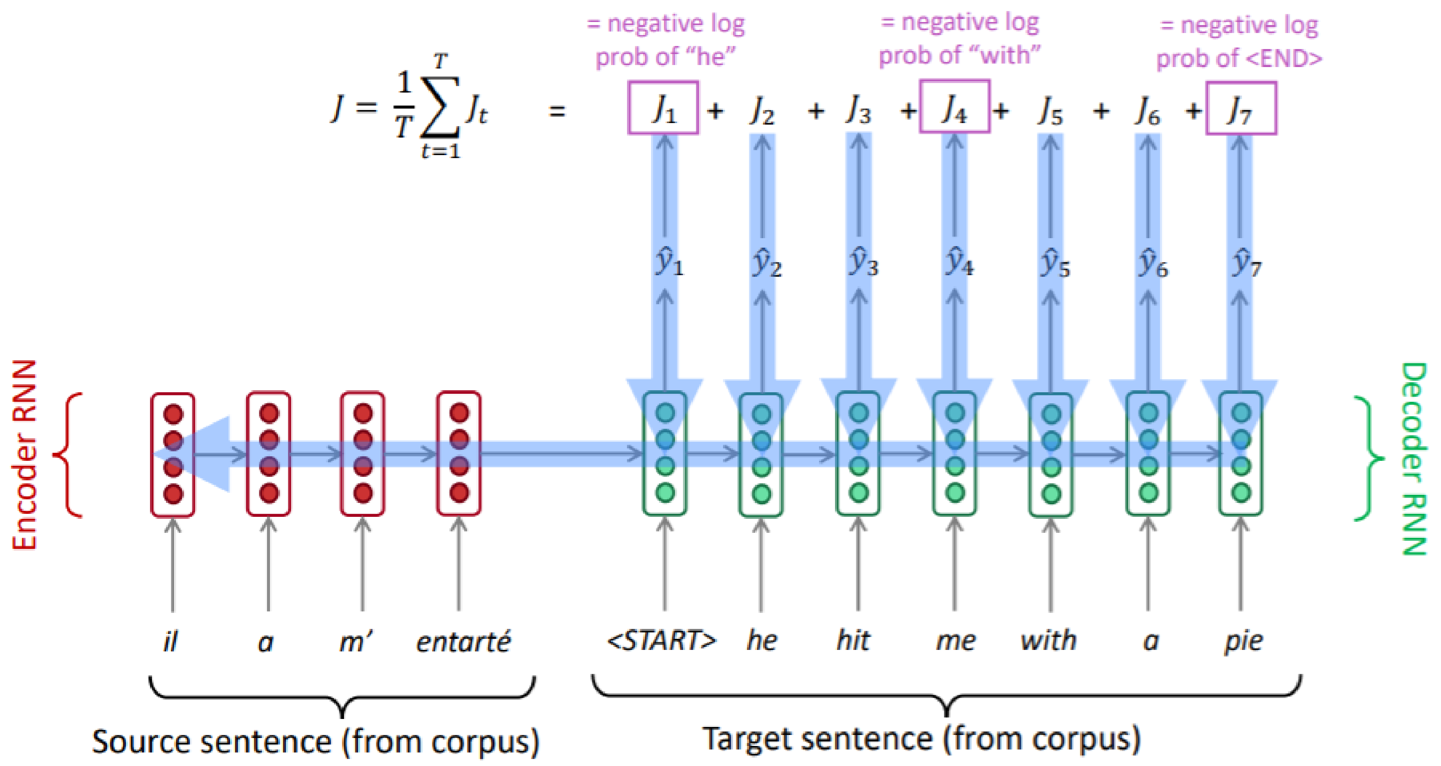
Neural Machine Translation (NMT)

NMT directly calculates $P(y|x)$:

$$P(y|x) = P(y_1|x)\,P(y_2|y_1, x)\,P(y_3|y_1, y_2, x) \ldots \underbrace{P(y_T|y_1, \ldots, y_{T-1}, x)}_{\text{Probability of next target word, given target words so far and source sentence } x}$$

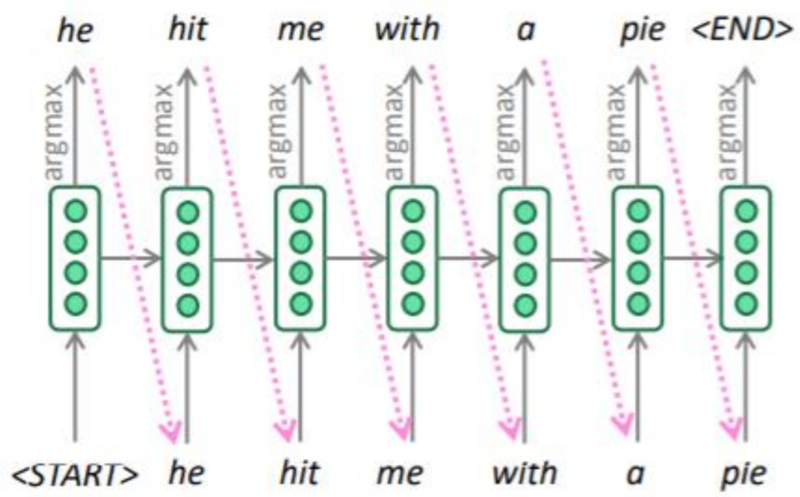
요약하자면 조건부 언어모델!

Training a Neural Machine Translation system



End- to-End
시스템 전반적으로 최적화!

Greedy decoding



- Greedy decoding has no way to undo decisions!
  - Input: *il a m'entarté* (*he hit me with a pie*)
  - → *he* ____
  - → *he hit* ____
  - → *he hit a* ____ (whoops! no going back now…)

1. Exhaustive search decoding

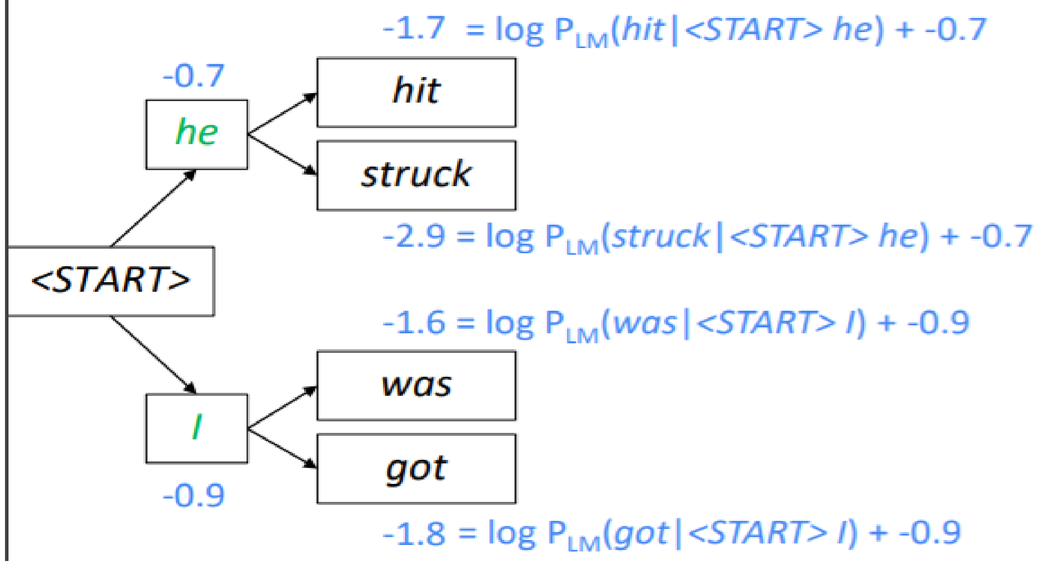
$$P(y|x) = P(y_1|x)\,P(y_2|y_1,x)\,P(y_3|y_1,y_2,x)\ldots,P(y_T|y_1,\ldots,y_{T-1},x)$$
$$= \prod_{t=1}^{T} P(y_t|y_1,\ldots,y_{t-1},x)$$

2. Beam search decoding

$$\text{score}(y_1,\ldots,y_t) = \log P_{\text{LM}}(y_1,\ldots,y_t|x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1,\ldots,y_{i-1},x)$$

Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



Beam search decoding: example

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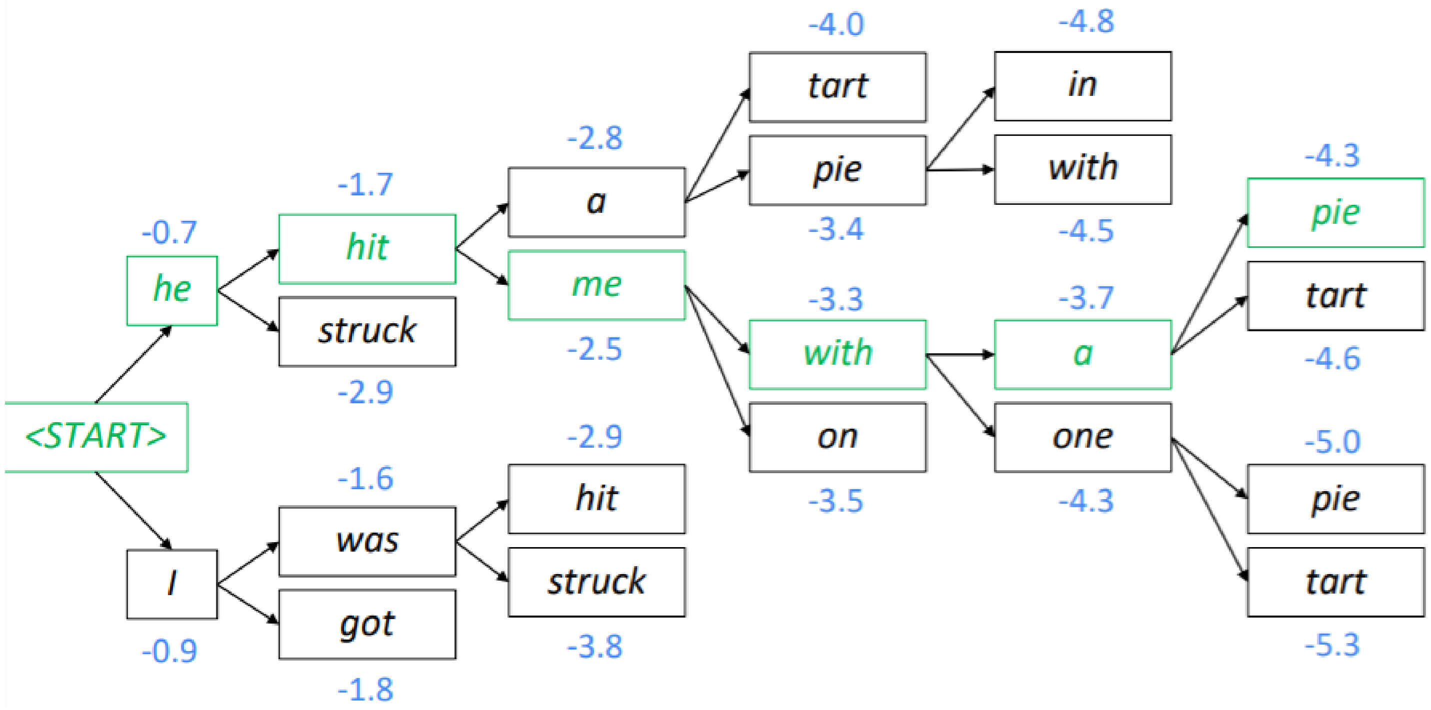
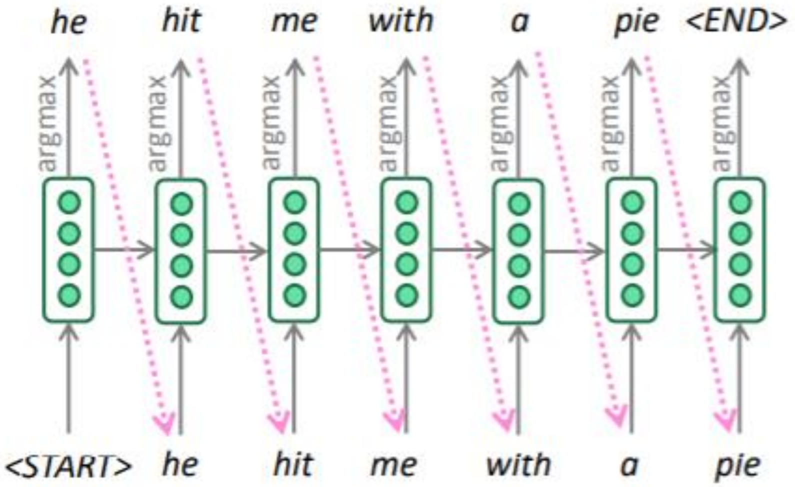


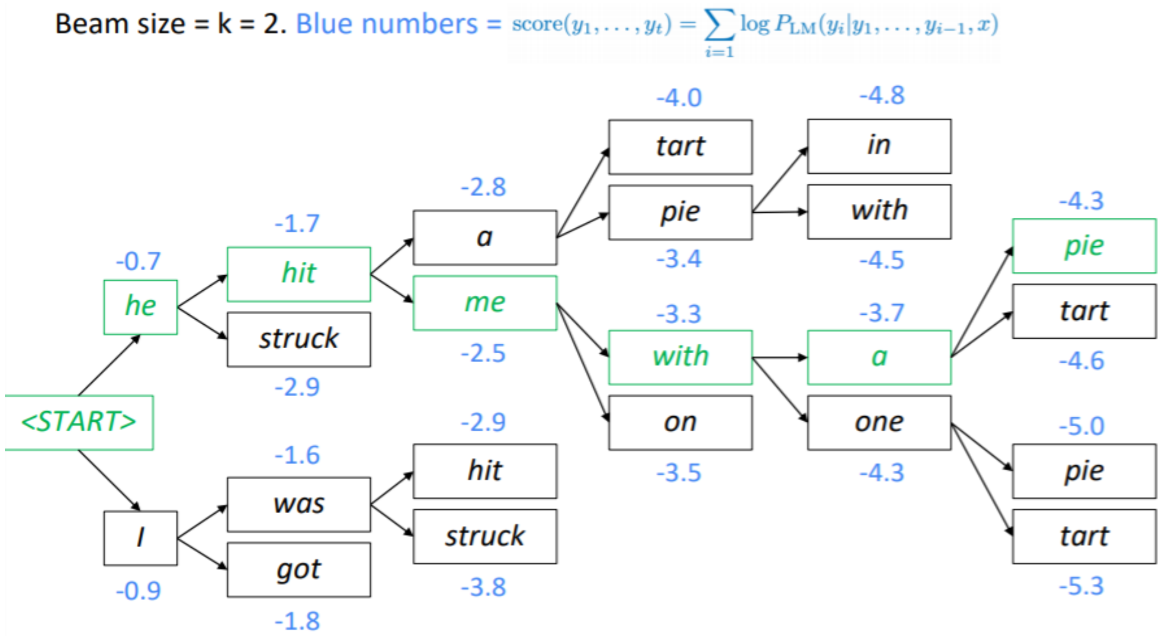
Beam search decoding: stopping criterion

Greedy decoding

vs

Beam search decoding





Beam search decoding: finishing up

$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t | x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

$$\downarrow$$

$$\frac{1}{t} \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$$

Advantages, Disadvantages of NMT

Advantages

1. 더 나은 성능
2. Single neural network to be optimized end-to-end
   (하부구조가 개별적으로 optimized될 필요 X)
3. 인간의 노력 덜 필요

Disadvantages

1. Hard to debug
2. Difficult to control

How do we evaluate Machine Translation? BLEU (Bilingual Evaluation Understudy)

- `예측된 sentence`: **빛이 쐬는** 노인은 **완벽한** 어두운곳에서 **잠든 사람과 비교할 때** 강박증이 **심해질** 기회가 **훨씬 높았다**
- `true sentence`: **빛이 쐬는** 사람은 **완벽한** 어둠에서 **잠든 사람과 비교할 때** 우울증이 **심해질** 가능성이 **훨씬 높았다**

- 1-gram precision: $\frac{\text{일치하는}1-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}1-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{10}{14}$
- 2-gram precision: $\frac{\text{일치하는}2-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}2-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{5}{13}$
- 3-gram precision: $\frac{\text{일치하는}3-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}3-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{2}{12}$
- 4-gram precision: $\frac{\text{일치하는}4-gram\text{의 수(예측된 }sentence\text{중에서)}}{\text{모든}4-gram\text{쌍 (예측된 }sentence\text{중에서)}} = \frac{1}{11}$

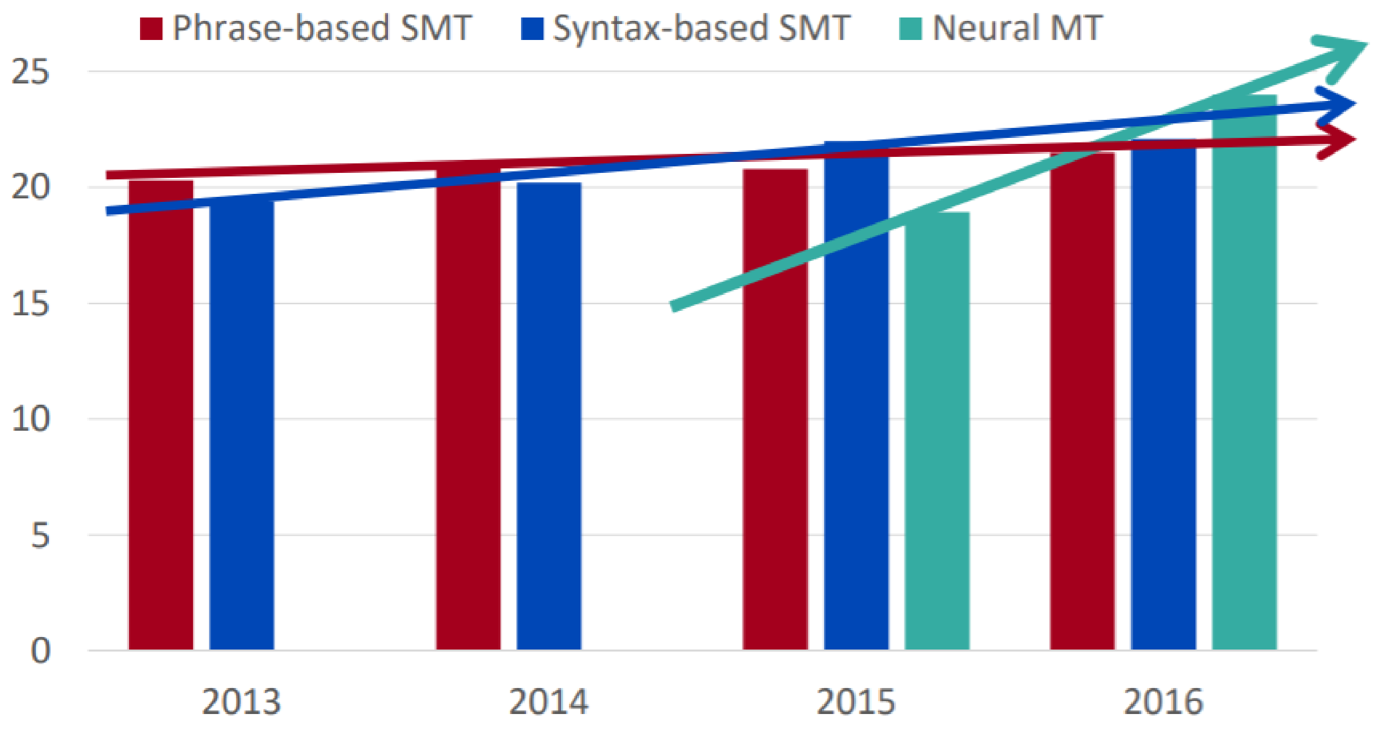
$$(\prod_{i=1}^{4} precision_i)^{\frac{1}{4}} = (\frac{10}{14} \times \frac{5}{13} \times \frac{2}{12} \times \frac{1}{11})^{\frac{1}{4}}$$

$$BLEU = min(1, \frac{output\ length(\text{예측 문장})}{reference\ length(\text{실제 문장})})(\prod_{i=1}^{4} precision_i)^{\frac{1}{4}}$$

$$= min(1, \frac{14}{14}) \times (\frac{10}{14} \times \frac{5}{13} \times \frac{2}{12} \times \frac{1}{11})^{\frac{1}{4}}$$

How do we evaluate Machine Translation?

BLEU (**Bi**lingual **E**valuation **U**nderstudy)



NMT : the biggest success story of NLP Deep Learning

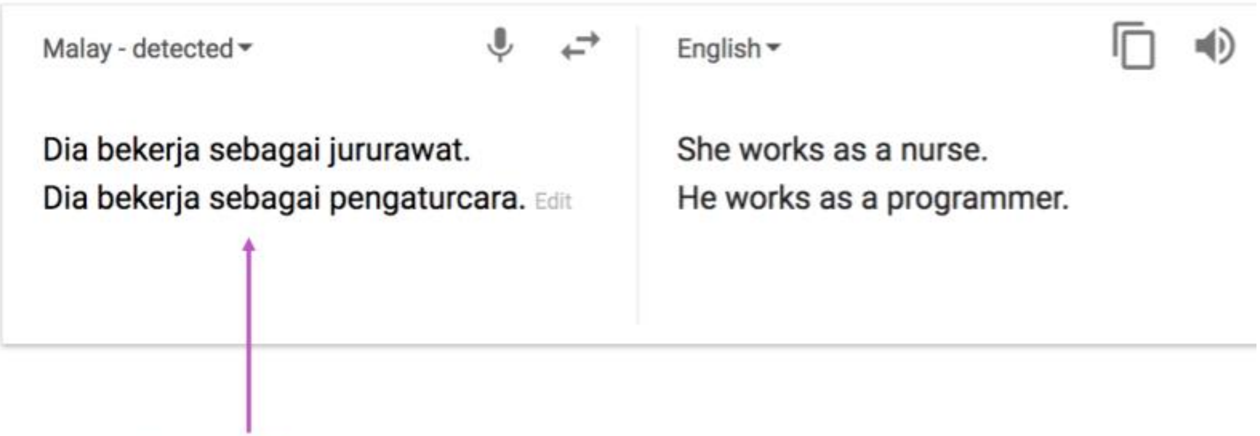
- **2014**: First seq2seq paper published
- **2016**: Google Translate switches from SMT to NMT

하지만 한계점이 존재..

1. 목표 어휘에 없는 단어 생성 불가
2. 도메인 불일치
3. 긴 텍스트에 대한 문맥 유지
4. 리소스가 부족한 언어 쌍

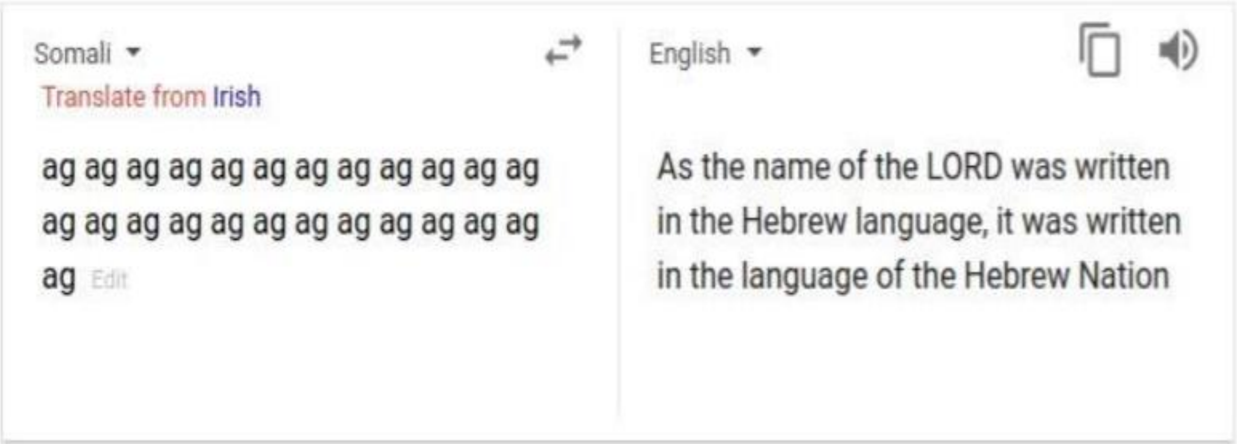
So is Machine Translation solved?

?



Didn’t specify gender

So is Machine Translation solved?



→ **ATTENTION**

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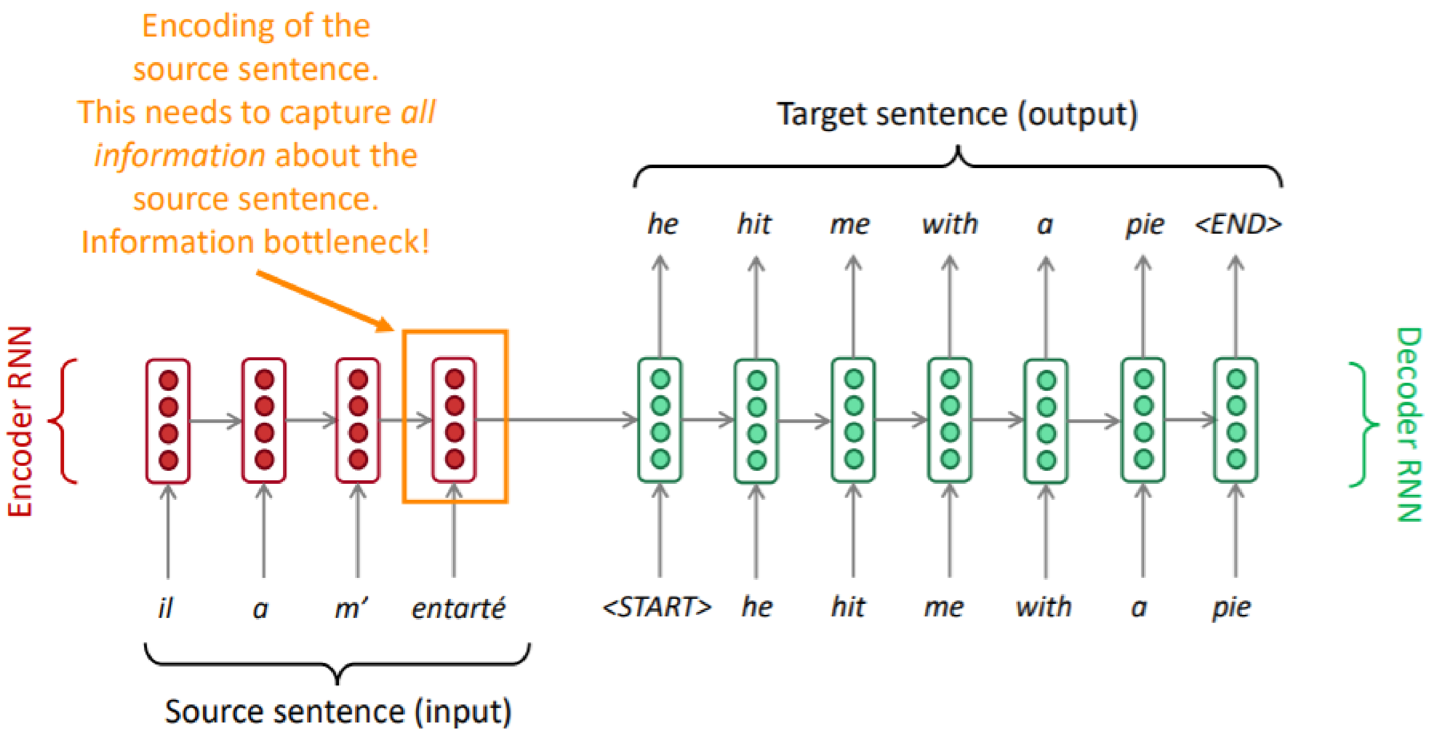
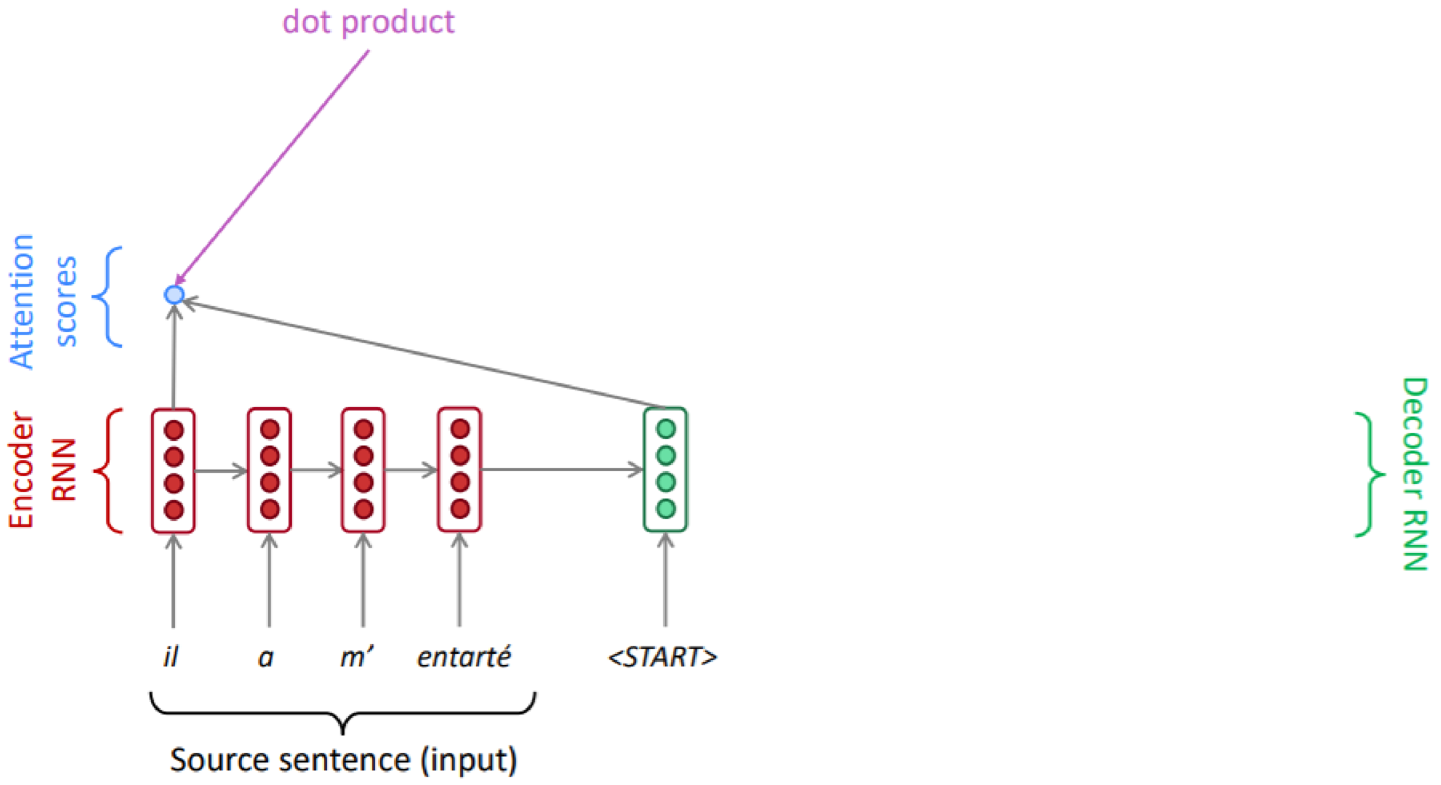
Attention

Sequence-to-sequence : the bottleneck problem

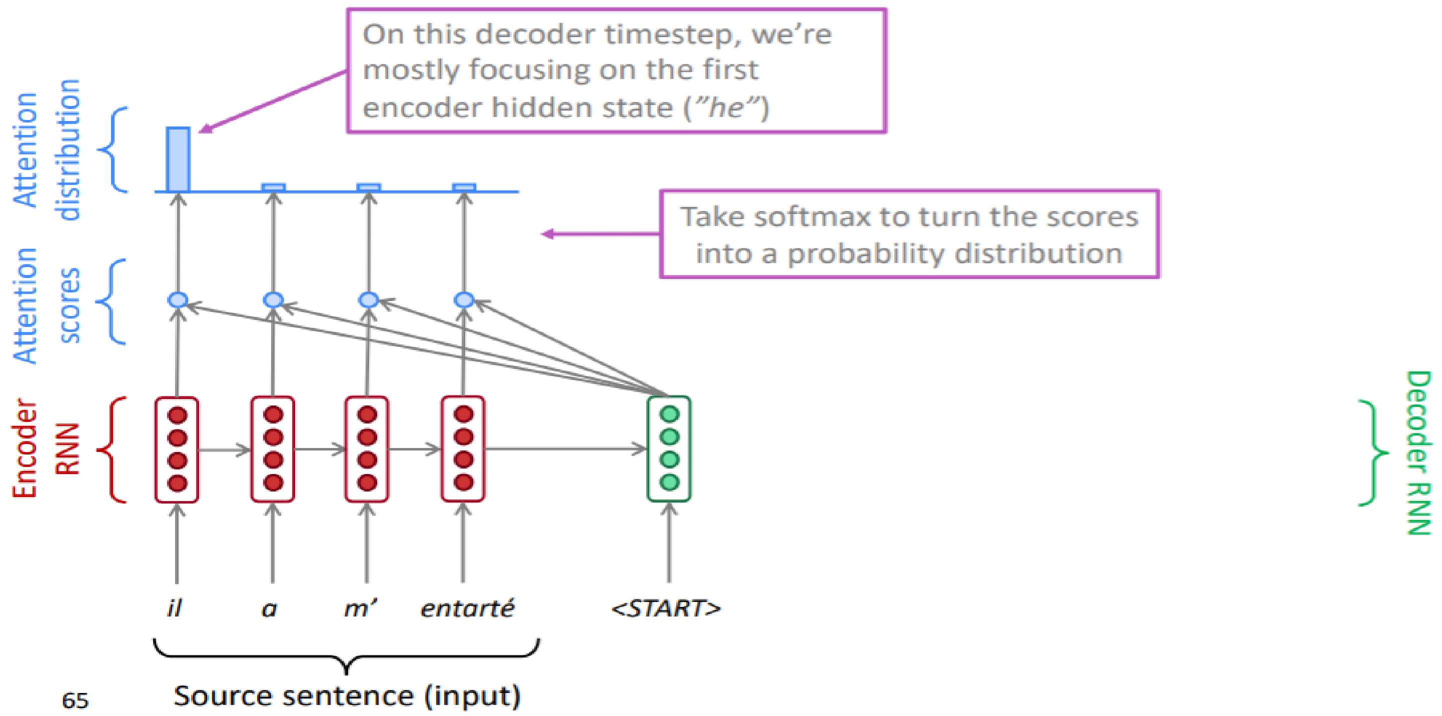


맨 끝에서 모든 정보를 캡쳐 강요
→ 너무 많은 압력 → 병목문제

Sequence-to-sequence with attention

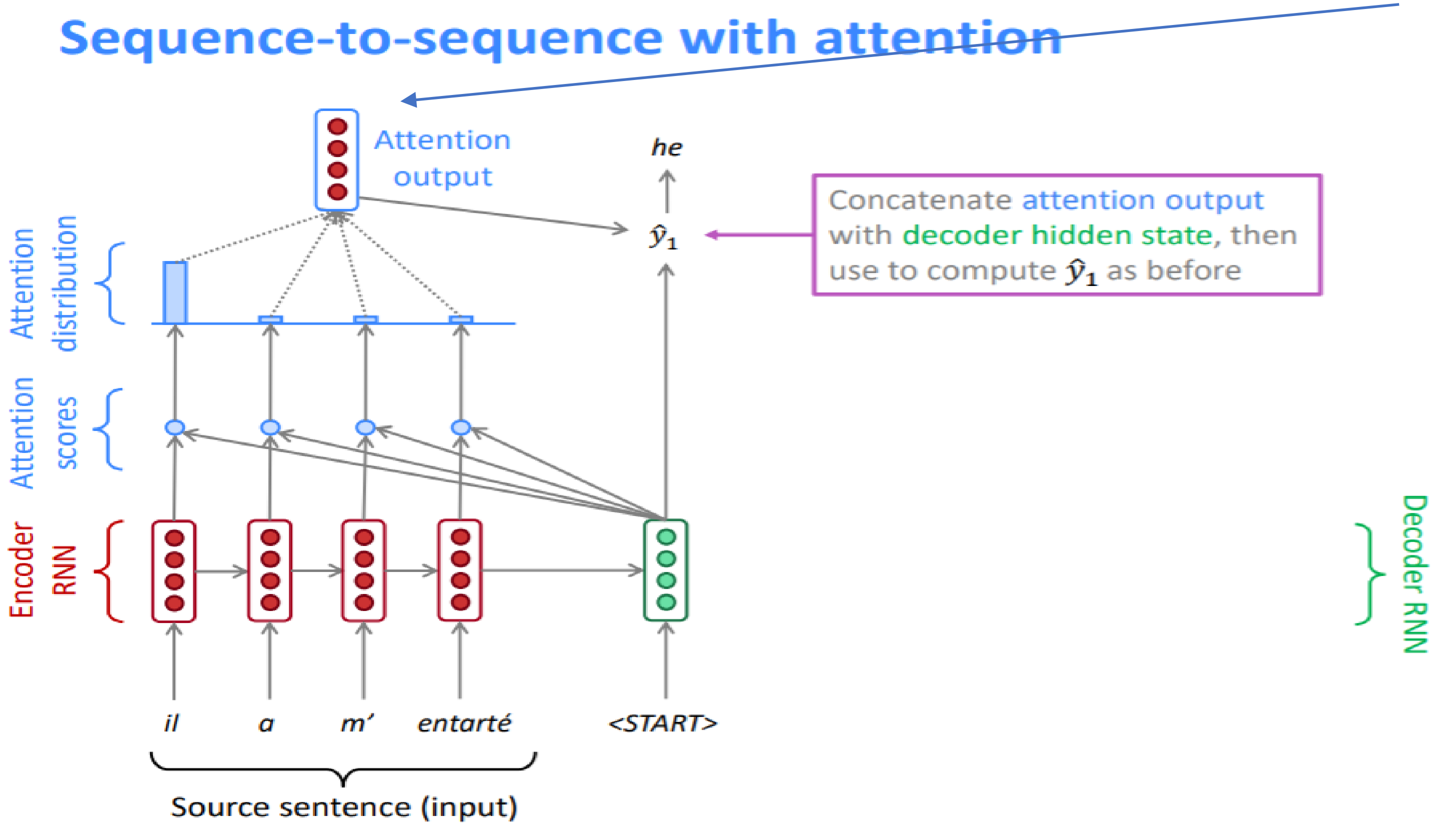


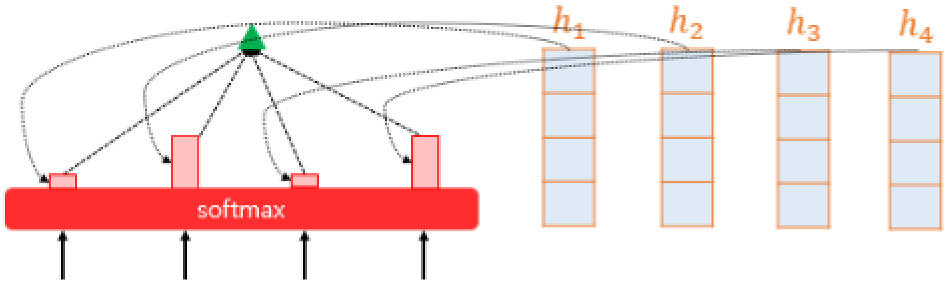
Sequence-to-sequence with attention



모든 인코더의 step마다 반복!
Attention을 주는 것

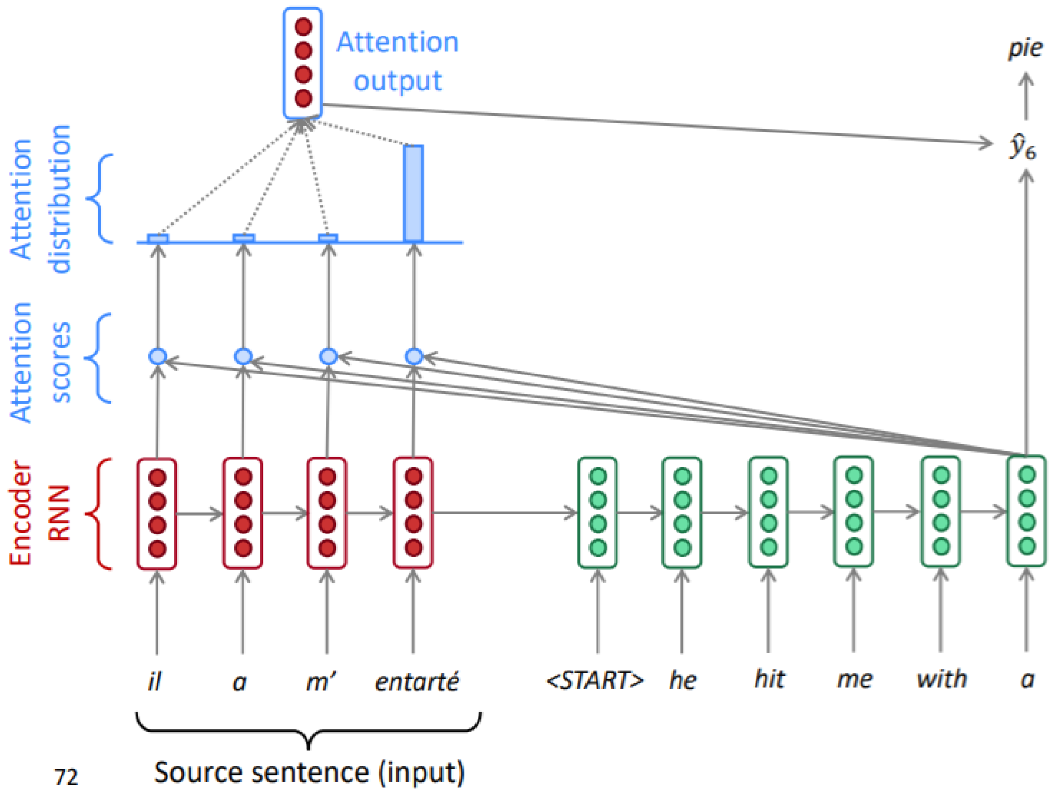
Sequence-to-sequence with attention





Attention의 output과 decode의 hidden state의 결합 → y1(hat)을 계산

Sequence-to-sequence with attention



decoder에서도 같은 행동을 반복!

Attention : in equations

- We have encoder hidden states $h_1, \dots, h_N \in \mathbb{R}^h$
- On timestep *t*, we have decoder hidden state $s_t \in \mathbb{R}^h$
- We get the attention scores $\boldsymbol{e}^t$ for this step:

$$\boldsymbol{e}^t = [\boldsymbol{s}_t^T \boldsymbol{h}_1, \dots, \boldsymbol{s}_t^T \boldsymbol{h}_N] \in \mathbb{R}^N$$

- We take softmax to get the attention distribution α^t for this step (this is a probability distribution and sums to 1)

$$\alpha^t = \mathrm{softmax}(\boldsymbol{e}^t) \in \mathbb{R}^N$$

- We use α^t to take a weighted sum of the encoder hidden states to get the attention output $\boldsymbol{a}_t$

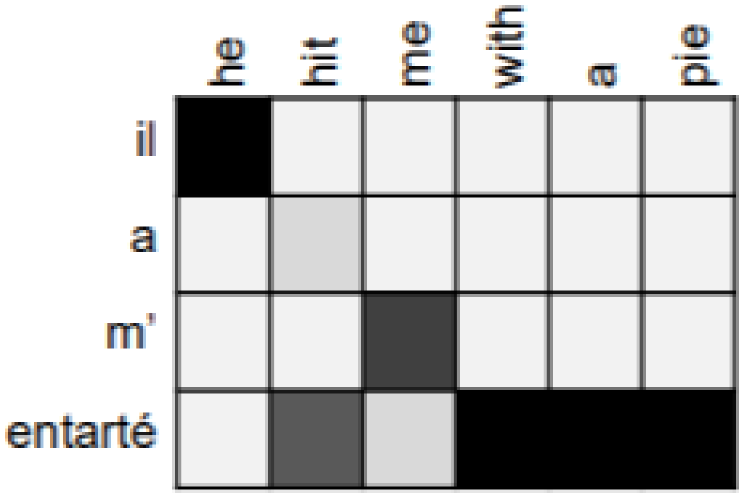
$$\boldsymbol{a}_t = \sum_{i=1}^{N} \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

- Finally we concatenate the attention output $\boldsymbol{a}_t$ with the decoder hidden state s_t and proceed as in the non-attention seq2seq model

$$[\boldsymbol{a}_t; \boldsymbol{s}_t] \in \mathbb{R}^{2h}$$

1. Encoder hidden states
2. Decoder hidden state
3. Softmax
4. Attention output
5. Y hat

Attention is great



1. NMT 성능을 향상시킴
2. 병목문제 해결
3. 기울기 소실 문제 해결
4. 추적 가능성

참고 자료

https://donghwa-kim.github.io/BLEU.html
https://www.programmersought.com/article/89135232797/
https://jeongukjae.github.io/posts/cs224n-lecture-8-machine-translation,-seq2seq,-attention/
https://pongdangstory.tistory.com/424
https://wikidocs.net/22893
자언어->코드 : https://blogs.oracle.com/meena/code-generation-using-lstm-long-short-term-memory-rnn-network

Q & A

들어주셔서 감사합니다.