COS 484

Natural Language Processing

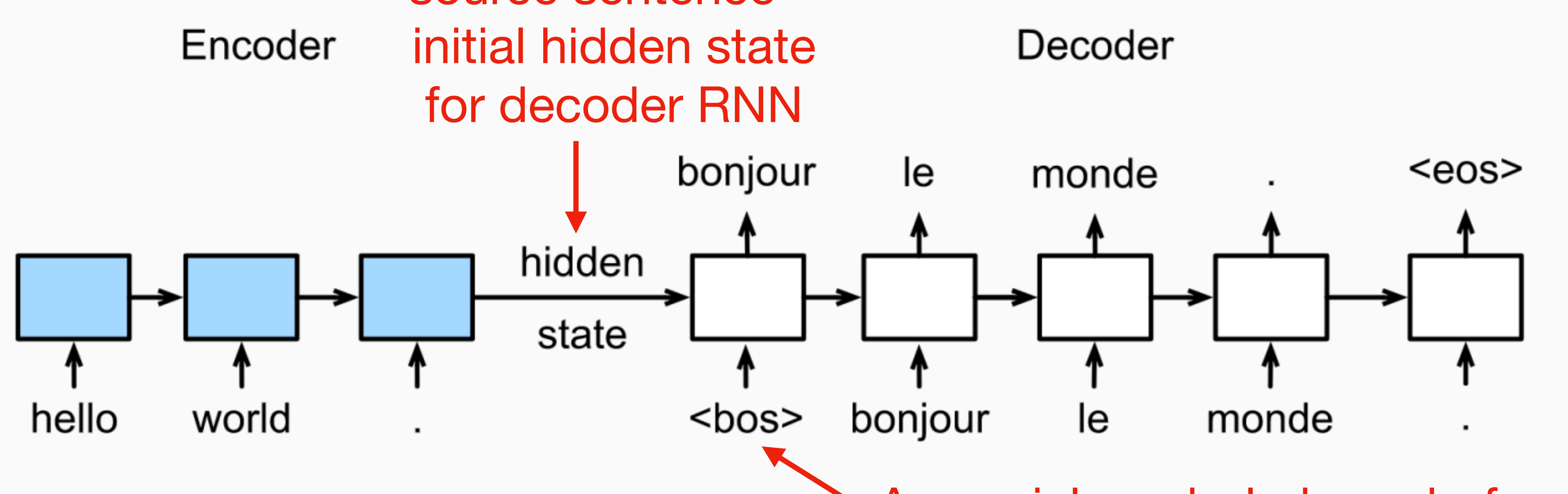
L12: Seq2seq models + attention

Spring 2024

(Some slides adapted from Chris Manning)

The sequence-to-sequence model (seq2seq)

Encoding of source sentence = initial hidden state for decoder RNN



A special symbol <bos> before generating the first word

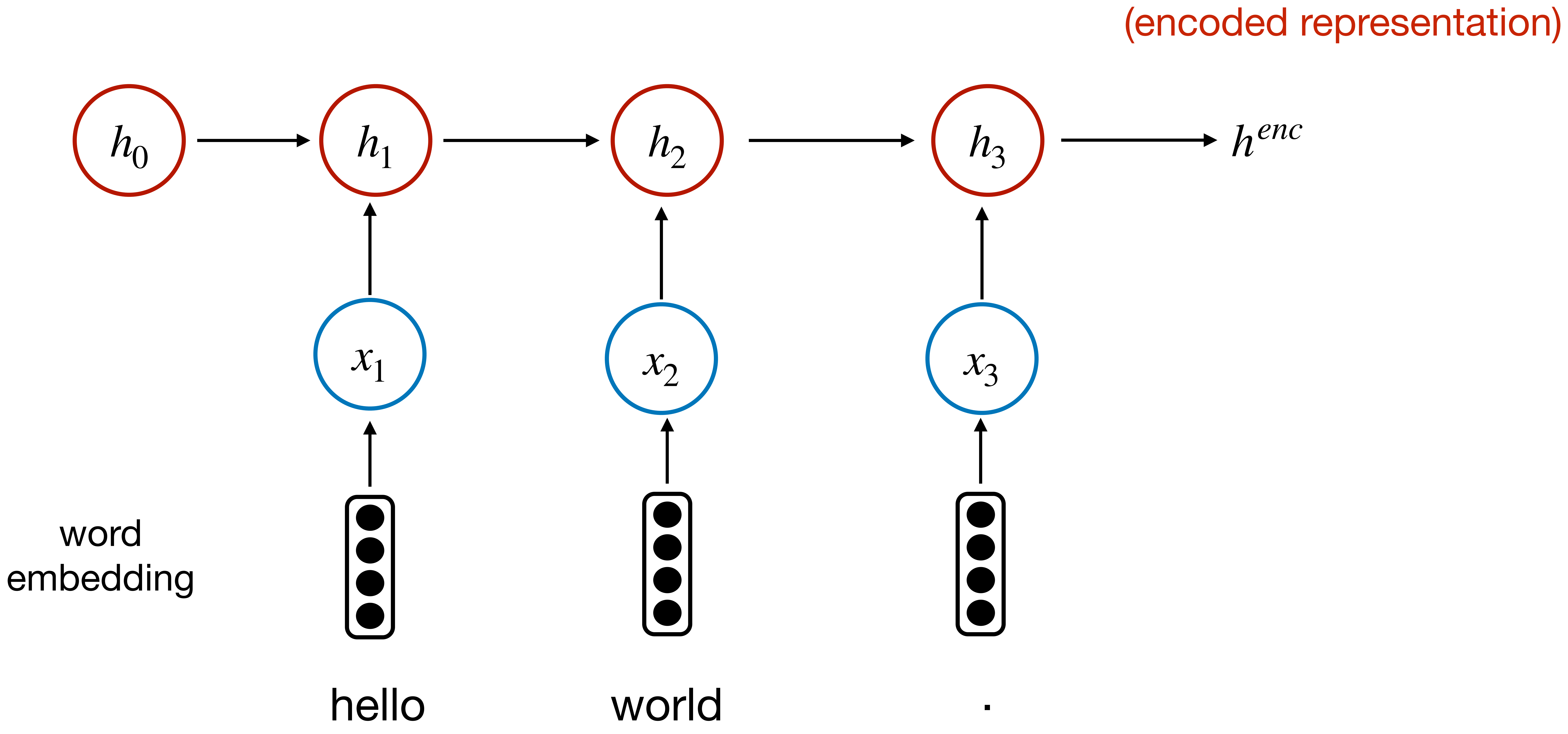
It is called an **encoder-decoder** architecture

- The encoder is an RNN to read the input sequence (source language)
- The decoder is another RNN to generate output word by word (target language)

Image: https://d2l.ai/chapter_recurrent-modern/seq2seq.html

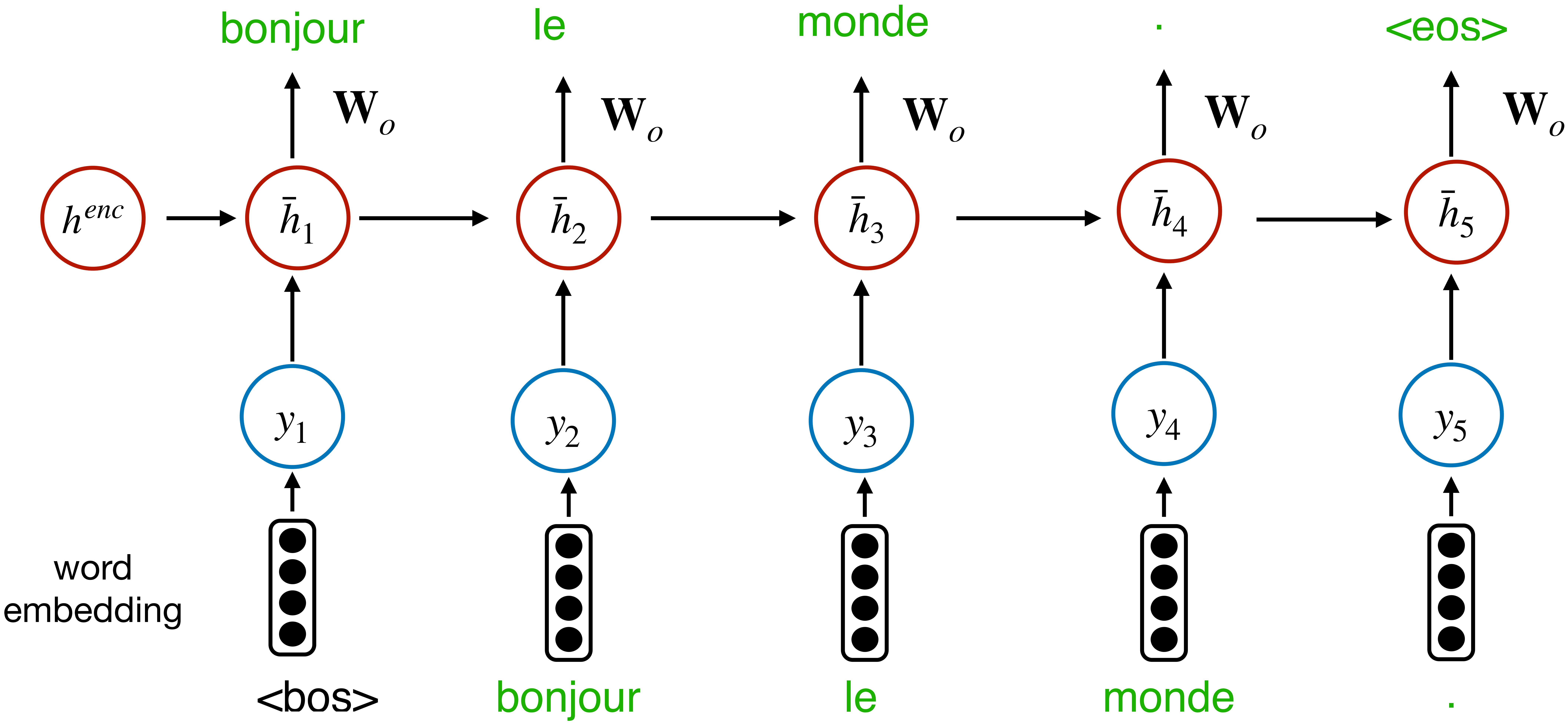
Seq2seq: Encoder

Sentence: hello world .



Seq2seq: Decoder

- A **conditional** language model

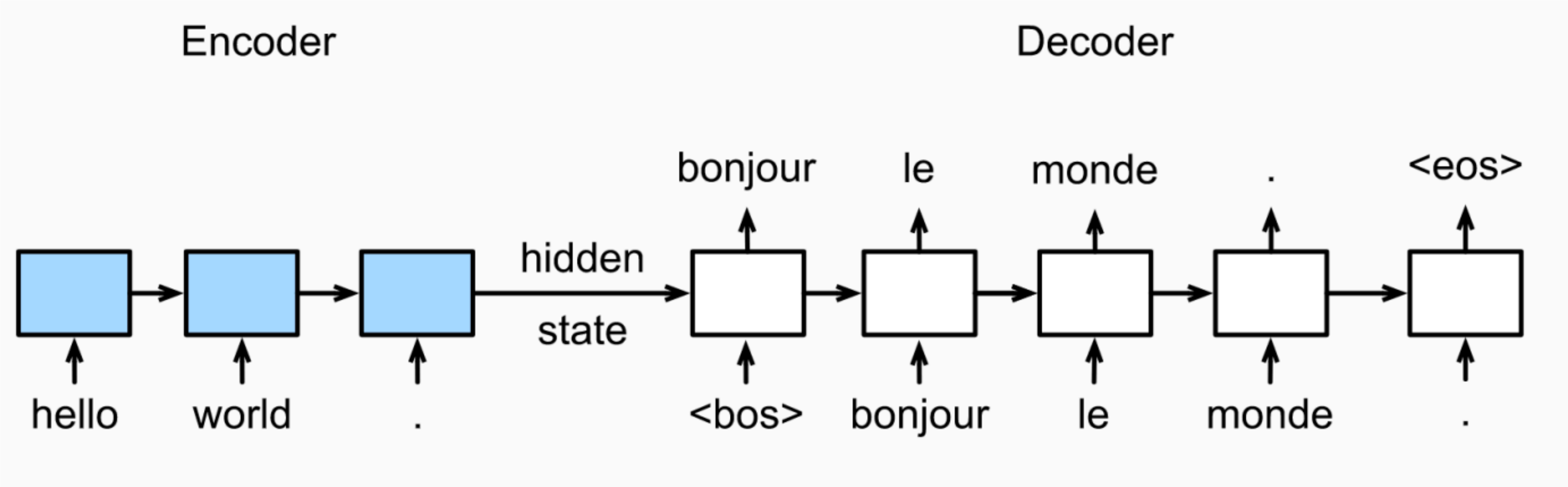


Seq2seq: Decoder

- A **conditional** language model
  - It is a **language model** because the decoder is predicting the next word of the target sentence
  - **Conditional** because the predictions are also conditioned on the source sentence through h^{enc}
- NMT directly calculates $P(\mathbf{w}^{(t)} \mid \mathbf{w}^{(s)})$
  - Denote $\mathbf{w}^{(t)} = y_1, \ldots, y_T$

$$P(\mathbf{w}^{(t)} \mid \mathbf{w}^{(s)}) = P(y_1 \mid \mathbf{w}^{(s)})P(y_2 \mid y_1, \mathbf{w}^{(s)})P(y_3 \mid y_1, y_2, \mathbf{w}^{(s)})\ldots P(y_T \mid y_1, \ldots, y_{T-1}, \mathbf{w}^{(s)})$$

Understanding seq2seq

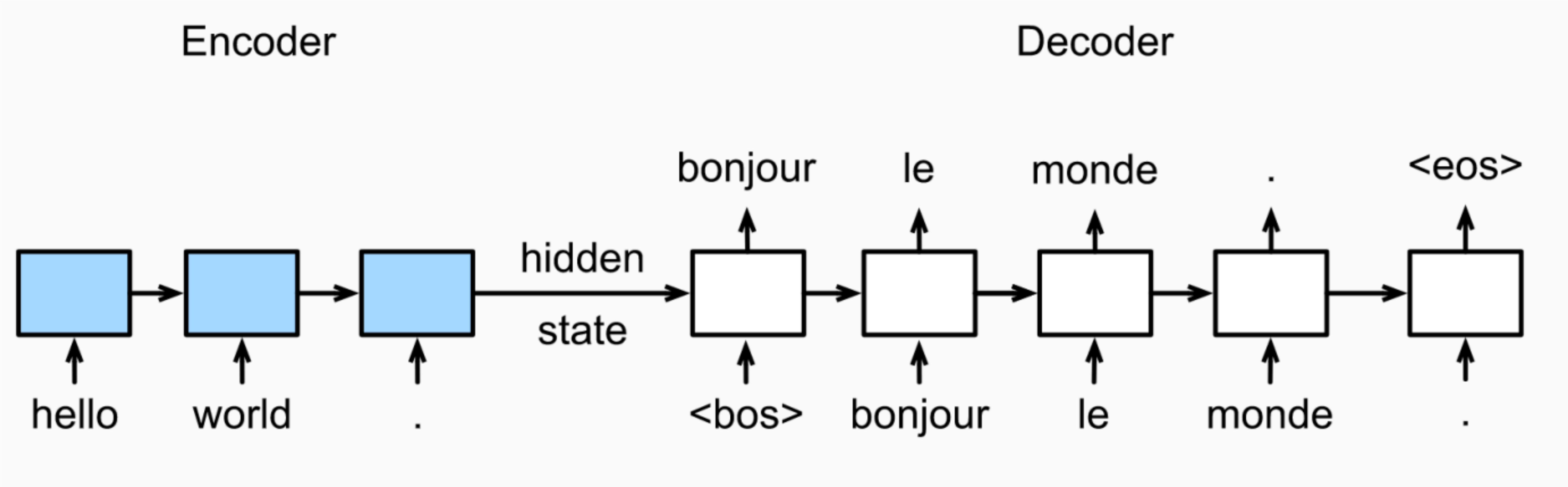


Which of the following is correct?

- (A) We can use bidirectional RNNs for both encoder and decoder
- (B) The decoder has more parameters because of the output matrix $\mathbf{W}_o$
- (C) The encoder and decoder have separate word embeddings
- (D) The encoder and decoder's parameters are optimized together

Both (C) and (D) are correct.

Understanding seq2seq



Encoder RNN:

- word embeddings $\mathbf{E}^{(s)}$ for source language
- RNN parameters, e.g., $\{\mathbf{W}, \mathbf{U}, \mathbf{b}\}$ for simple RNNs and 4x parameters for LSTMs
- Encoder RNN can be bidirectional!

Decoder RNN:

- word embeddings $\mathbf{E}^{(t)}$ for target language
- RNN parameters, e.g., $\{\mathbf{W}, \mathbf{U}, \mathbf{b}\}$ for simple RNNs and 4x parameters for LSTMs
- Output embedding matrix $\mathbf{W}_o$ = can be tied with $\mathbf{E}^{(t)}$
- **Decoder RNN has to be unidirectional (left to right)!**

Training seq2seq models

- Training data: parallel corpus $\{(\mathbf{w}_i^{(s)}, \mathbf{w}_i^{(t)})\}$

- Minimize cross-entropy loss:

$$\sum_{t=1}^{T} -\log P(y_t \,|\, y_1, \ldots, y_{t-1}, \mathbf{w}^{(s)})$$

(denote $\mathbf{w}^{(t)} = y_1, \ldots, y_T$)

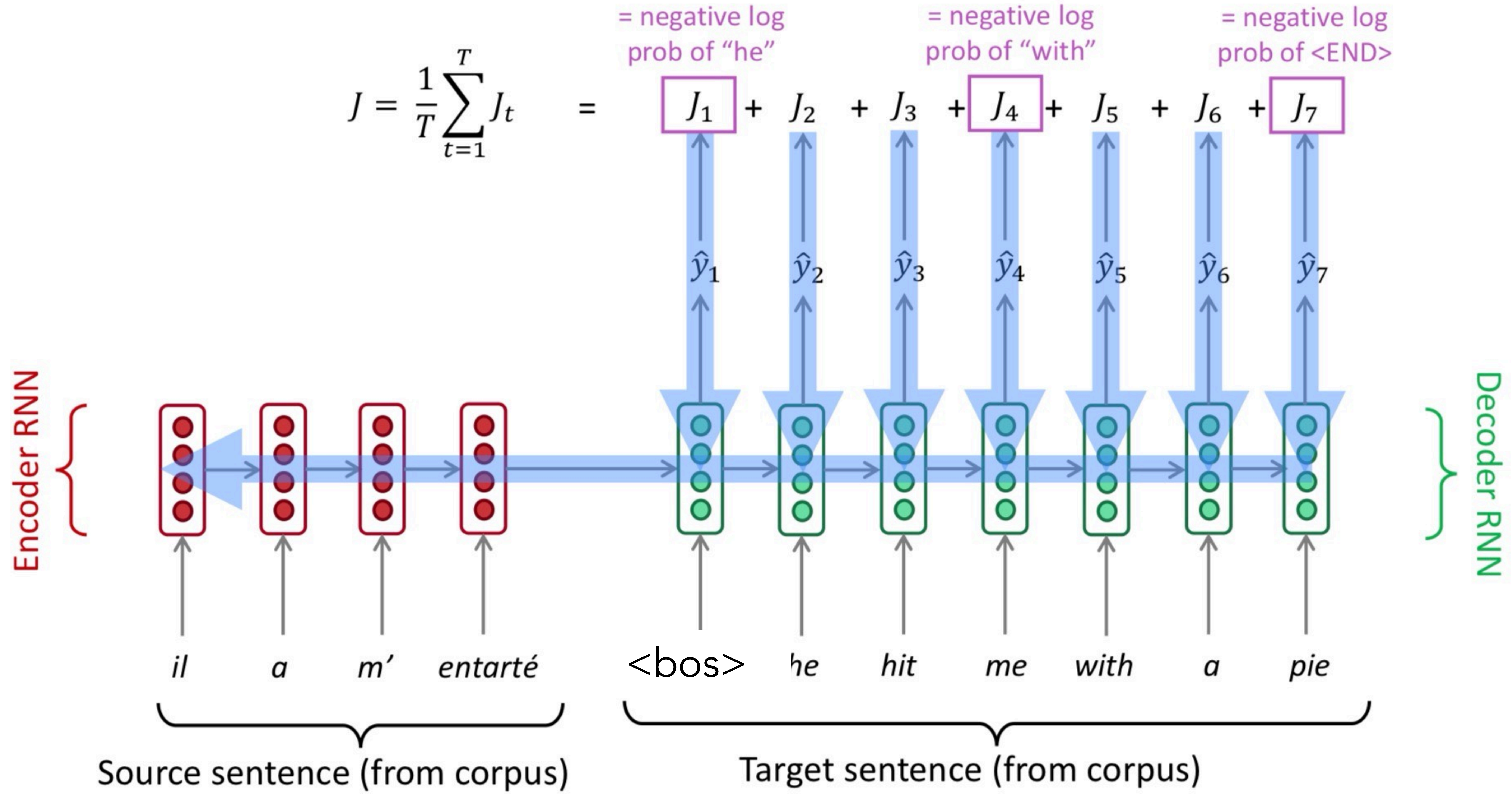
- Back-propagate gradients through both encoder and decoder

12M sentence pairs

French: bonjour le monde .

English: hello world .

Training seq2seq models

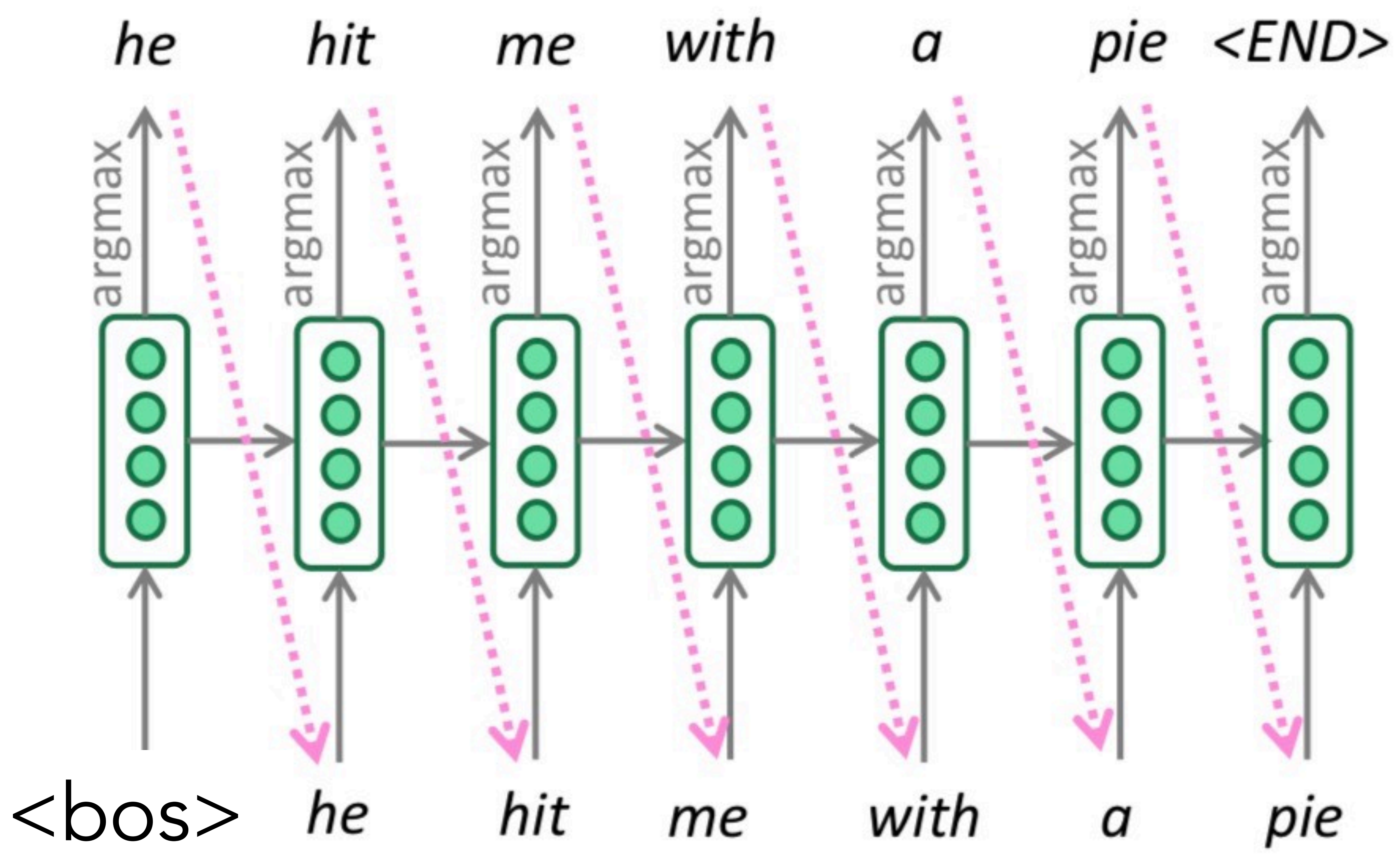


Seq2seq is optimized as a **single system.**
Backpropagation operates *"end-to-end"*.

Decoding seq2seq models

- Greedy decoding

  = Compute argmax at every step of decoder to generate word



- Exhaustive search is very expensive: $\arg\max_{y_1,\ldots,y_T} P(y_1,\ldots,y_T \mid \mathbf{w}^{(s)})$ - we even don't know what T is

Decoding with beam search

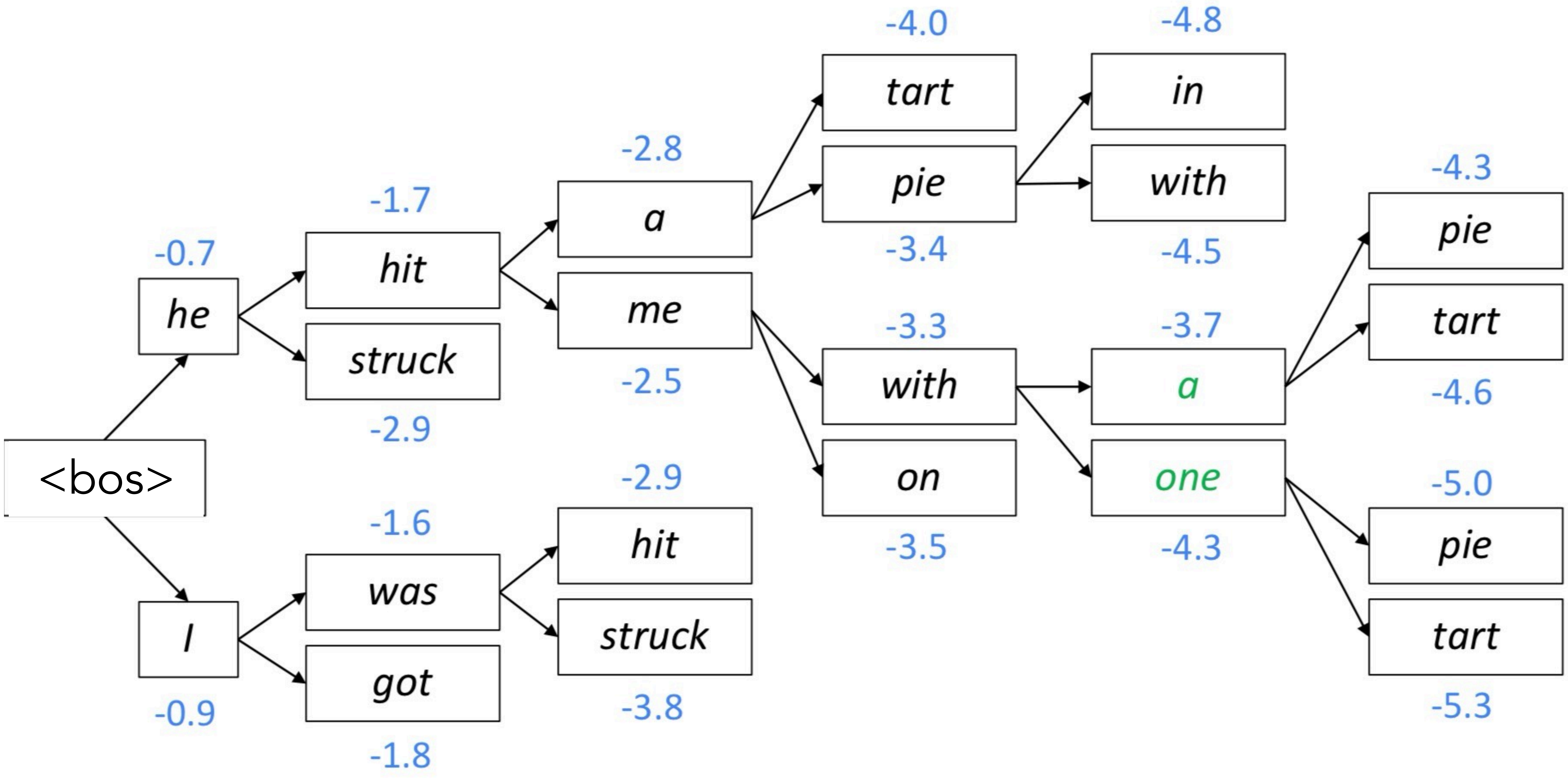
- At every step, keep track of the k most probable partial translations (hypotheses)
- Score of each hypothesis = log probability of sequence so far

$$\sum_{t=1}^{j} \log P(y_t \mid y_1, \ldots, y_{t-1}, \mathbf{w}^{(s)})$$

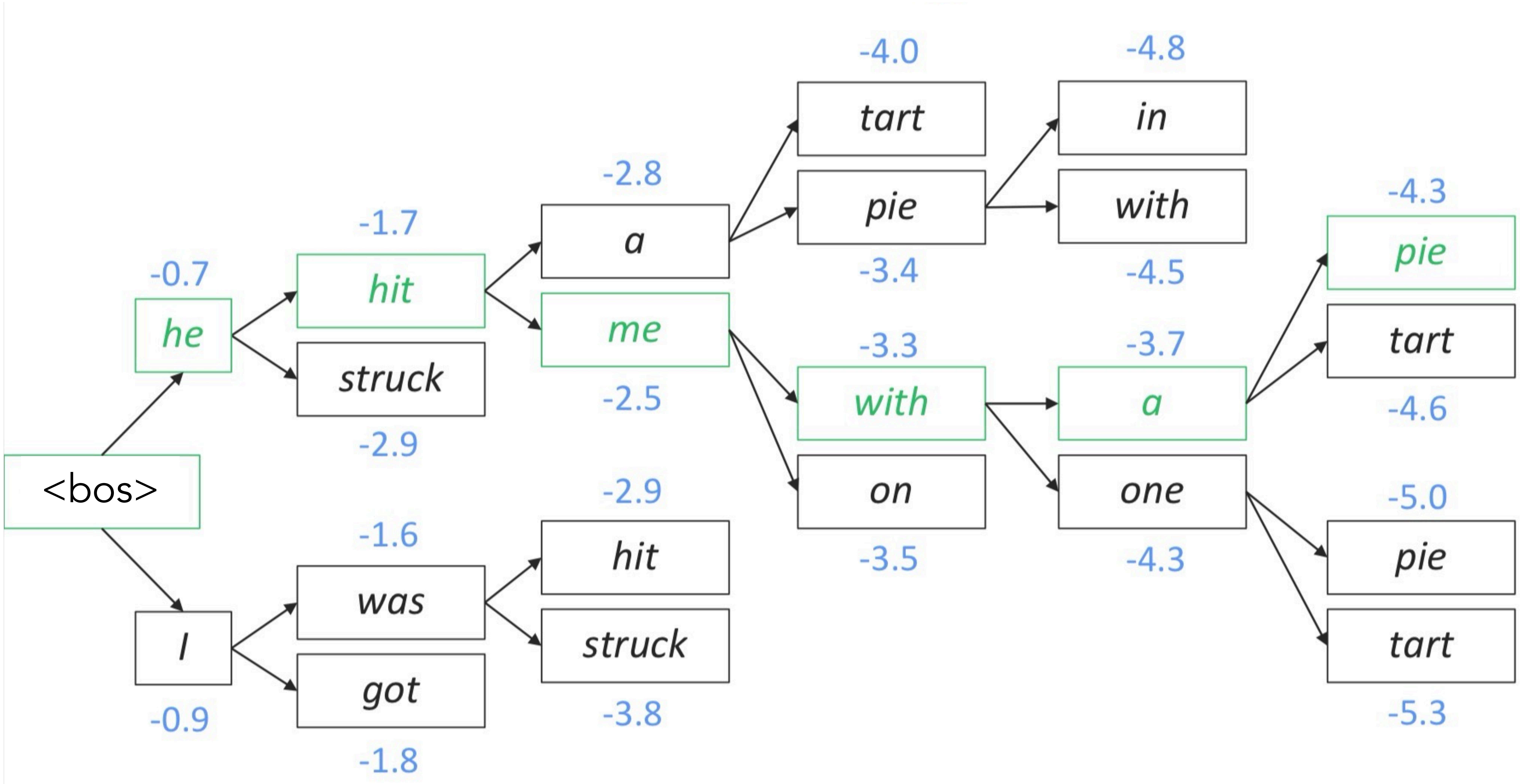
- Not guaranteed to be optimal
- Works better than greedy decoding in practice

Beam search

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P(y_i \mid y_1, \ldots, y_{i-1}, \mathbf{w}^{(s)})$



Beam search: Backtrack



Beam search: details

- Different hypotheses may produce $\langle eos \rangle$ token at different time steps
    - When a hypothesis produces $\langle eos \rangle$, stop expanding it and place it aside
- Continue beam search until:
    - All k hypotheses produce $\langle eos \rangle$ OR
    - Hit max decoding limit T
- Select top hypotheses using the *normalized* likelihood score

$$\frac{1}{T}\sum_{t=1}^{T}\log P(y_t \mid y_1, \ldots, y_{t-1}, \mathbf{w}^{(s)})$$

- Otherwise shorter hypotheses have higher scores

NMT vs SMT

Pros:

- Better performance (more **fluent**, better use of **context**, better use of **phrase similarities**)
- A **single neural network** to be optimized end-to-end (no individual subcomponents)
- **Less human engineering effort** - same method for all language pairs

Cons:

- NMT is **less interpretable**
- NMT is **difficult to control**

NMT: the first big success story of NLP deep learning

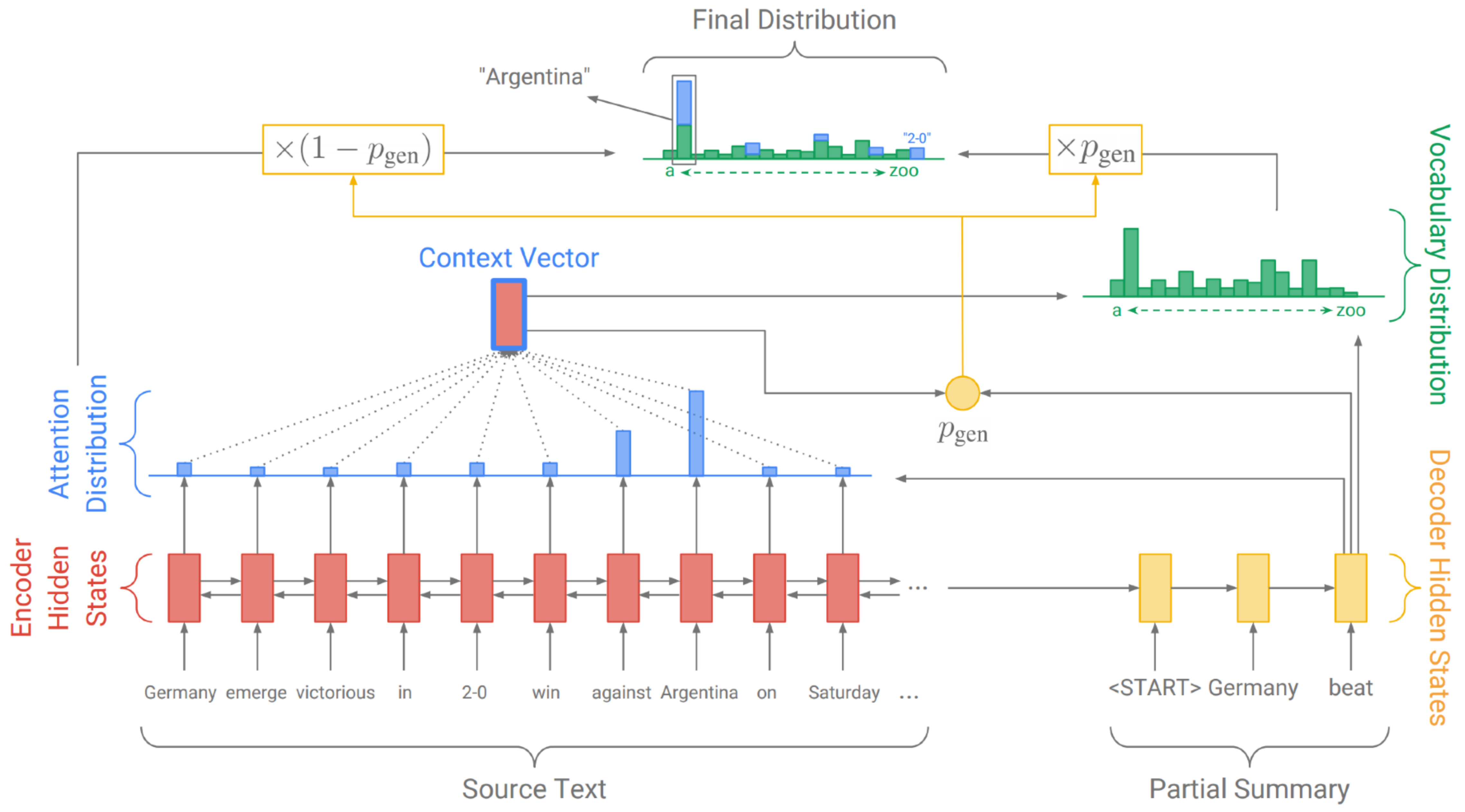
- 2014: First seq2seq paper published
- 2016: Google Translate switches from SMT to NMT - and by 2018 everyone has
- SMT systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a small group of engineers in a few months

Sequence-to-sequence is versatile

- Sequence-to-sequence is useful for more than just MT
- Many NLP tasks can be phrased as sequence-to-sequence
  - **Summarization** (long text → short text)
  - **Dialogue** (previous utterances → next utterance)
  - **Parsing** (input text → output parse as sequence)
  - **Code generation** (natural language → Python code)

Sequence-to-sequence is versatile

- Summarization



Source Text

munster have signed new zealand international francis *saili* on a two-year deal . utility back *saili* , who made his all blacks debut against argentina in 2013 , will move to the province later this year after the completion of his 2015 contractual commitments . the 24-year-old currently plays for *auckland-based* super rugby side the blues and was part of the new zealand under-20 side that won the junior world championship in italy in 2011 . *saili* 's signature is something of a coup for munster and head coach anthony foley believes he will be a great addition to their backline . francis *saili* has signed a two-year deal to join munster and will link up with them later this year . ' we are really pleased that francis has committed his future to the province , ' foley told munster 's official website . ' he is a talented centre with an impressive *skill-set* and he possesses the physical attributes to excel in the northern hemisphere . ' i believe he will be a great addition to our backline and we look forward to welcoming him to munster . ' *saili* has been capped twice by new zealand and was part of the under 20 side that won the junior championship in 2011 . *saili* , who joins all black team-mates dan carter , *ma'a nonu* , conrad smith and charles *piutau* in agreeing to ply his trade in the northern hemisphere , is looking forward to a fresh challenge . he said : ' i believe this is a fantastic opportunity for me and i am fortunate to move to a club held in such high regard , with values and traditions i can relate to from my time here in the blues . ' this experience will stand to me as a player and i believe i can continue to improve and grow within the munster set-up . ' as difficult as it is to leave the blues i look forward to the exciting challenge ahead . '

Reference summary

utility back francis *saili* will join up with munster later this year .
the new zealand international has signed a two-year contract .
saili made his debut for the all blacks against argentina in 2013 .

Sequence-to-sequence + attention summary

dutch international francis [UNK] has signed a two-year deal to join irish [UNK] super rugby side the blues .
[UNK] 's signature is something of a coup for munster and his head coach anthony foley believes he will be a great addition to their respective prospects .
[UNK] has been capped twice by new zealand .

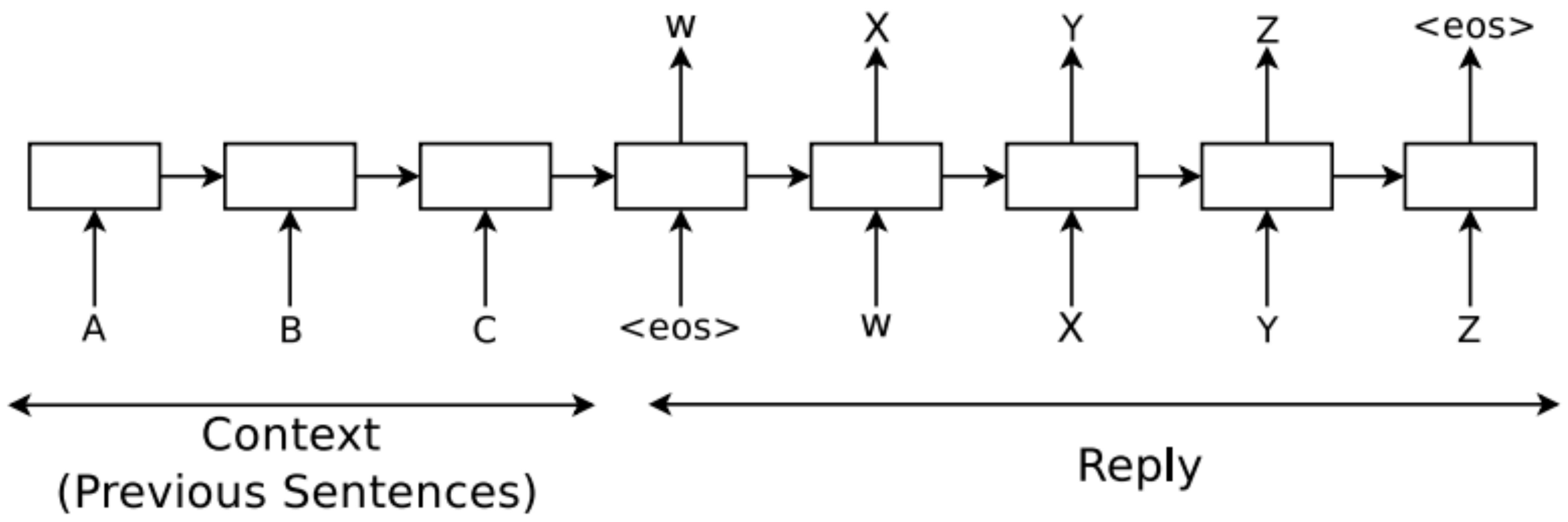
Pointer-generator summary

new zealand international francis *saili* will move to the province later this year .
utility back *saili* made his all blacks debut against argentina in 2013 .
utility back *saili* will move to the province later this year .

See et al., 2017: Get To The Point: Summarization with Pointer-Generator Networks

Sequence-to-sequence is versatile

- Dialogue

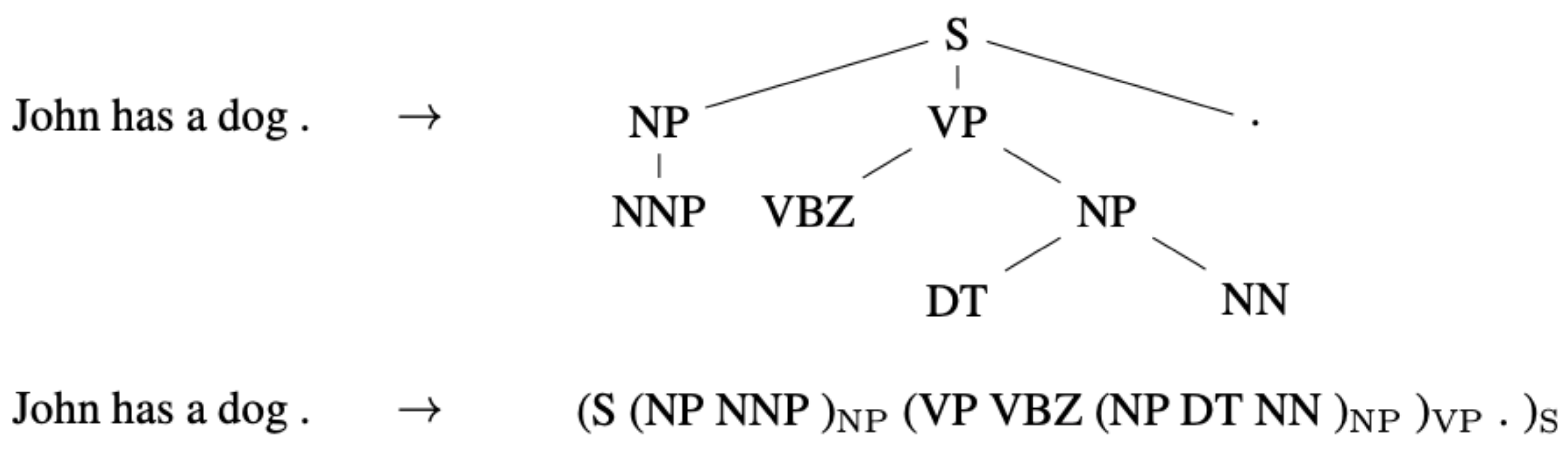


Human: *hello !*
Machine: *hello !*
Human: *how are you ?*
Machine: *i 'm good .*
Human: *what 's your name ?*
Machine: *i 'm julia .*
Human: *when were you born ?*
Machine: *july 20th .*
Human: *what year were you born ?*
Machine: *1977 .*
Human: *where are you from ?*

Vinyals and Le 2015: A Neuarl Conversational Model

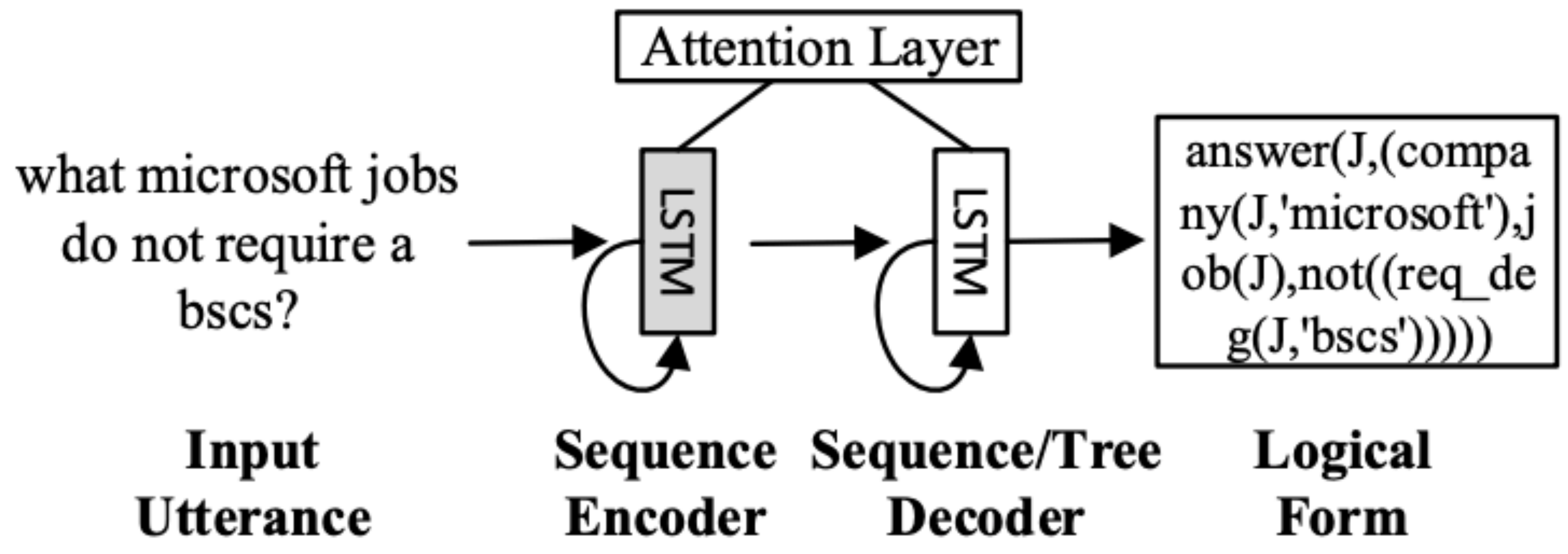
Sequence-to-sequence is versatile

- Parsing



Vinyals et al., 2015: Grammar as a Foreign Language

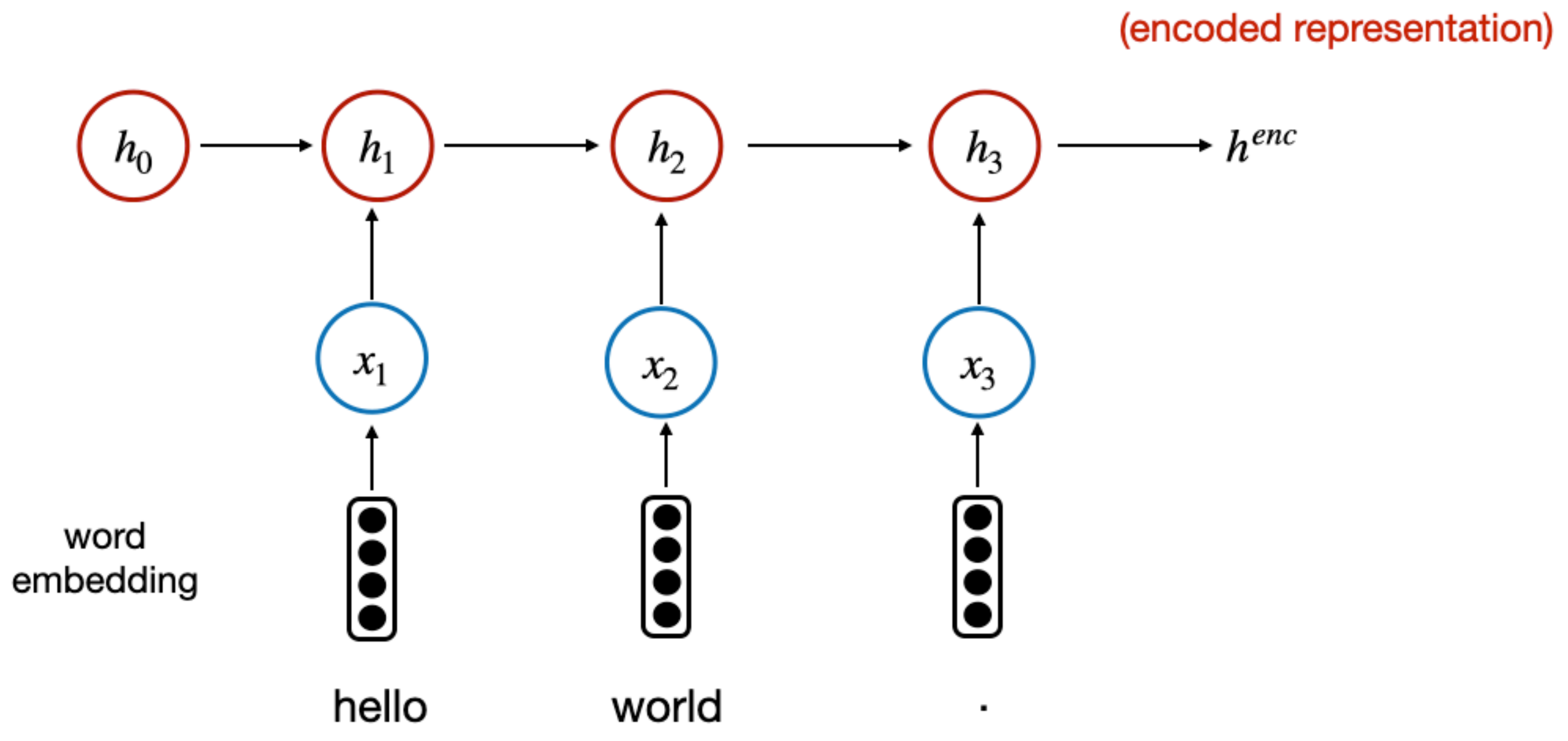
- Semantic parsing / code generation



Dong and Lapata, 2016: Language to Logical Form with Neural Attention

Subword tokenization

- So far, we have been always using words as the basic units
  - e.g., there is a pre-defined vocabulary V, and each word $w \in V$ has a word embedding



- How to represent all words even those we haven't seen in the training data?
  - A common solution: replace unknown words with a special <UNK> token
  - It is not a great solution for MT when you have a lot of unknown tokens

Byte pair encoding (BPE)

- Key idea: use subword units! Rare and unknown words are encoded as sequences of subword units

Original:	furiously	**Original:**	tricycles	**Original:**	nanotechnology
BPE:	`_fur iously`	**BPE:**	`_t ric y cles`	**BPE:**	`_n an ote chn ology`

Original:	`Completely preposterous suggestions`
BPE:	`_Comple t ely _prep ost erous _suggest ions`

Original:	`corrupted`	**Original:**	`1848 and 1852,`
BPE:	`_cor rupted`	**BPE:**	`_184 8 _and _185 2,`

- BPE = byte pair encoding (BPE) is a simple data compression technique (Gage, 1994)
- It was first introduced in NMT by (Sennirch et al., 2016) and achieved huge success
- Modern neural networks all build on subword units - besides BPE, there are also **unigram** and **wordpiece** tokenization algorithms

Byte pair encoding (BPE)

Algorithm 1 Byte-pair encoding (Sennrich et al., 2016; Gage, 1994)

```
Input: set of strings D, target vocab size k
procedure BPE(D, k)
    V ← all unique characters in D
            (about 4,000 in English Wikipedia)
    while |V| < k do                          ▷ Merge tokens
        t_L, t_R ← Most frequent bigram in D
        t_NEW ← t_L + t_R                     ▷ Make new token
        V ← V + [t_NEW]
        Replace each occurrence of t_L, t_R in
            D with t_NEW
    end while
    return V
end procedure
```

Initial vocabulary: characters

↓

Split each word into characters

Words in the data:

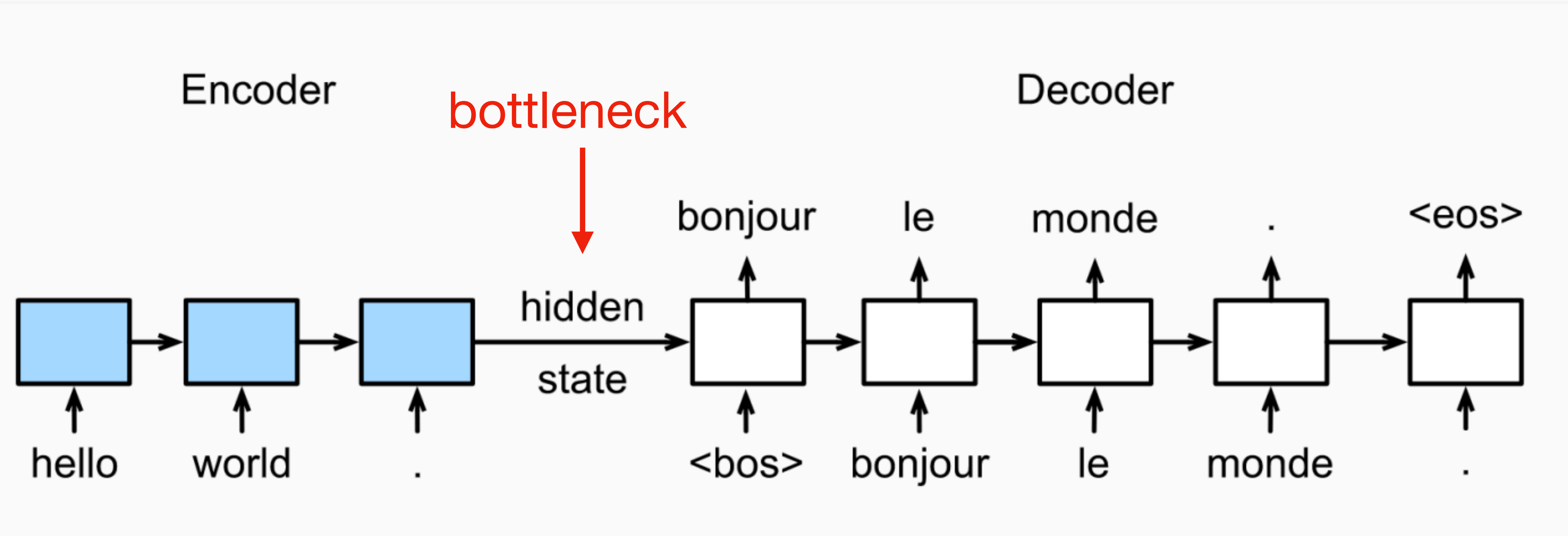
word	count
c a t	4
m a t	5
m a t s	2
m a t e	3
a t e	3
e a t	2

Current merge table:

(empty)

https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html#bpe

Sequence-to-sequence: the bottleneck

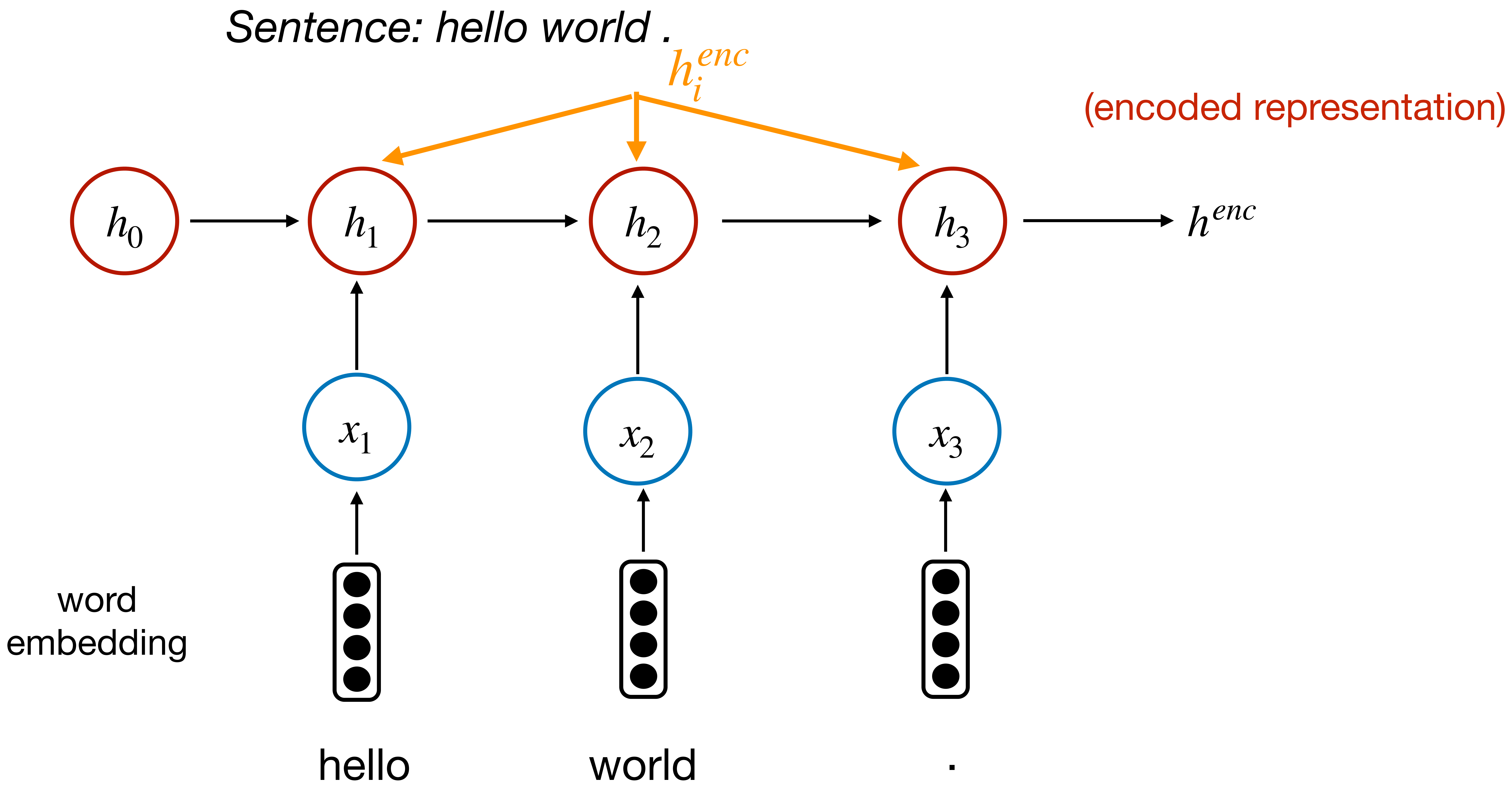


- A single encoding vector, h^{enc}, needs to capture all the information about source sentence
- Longer sequences can lead to vanishing gradients

Attention

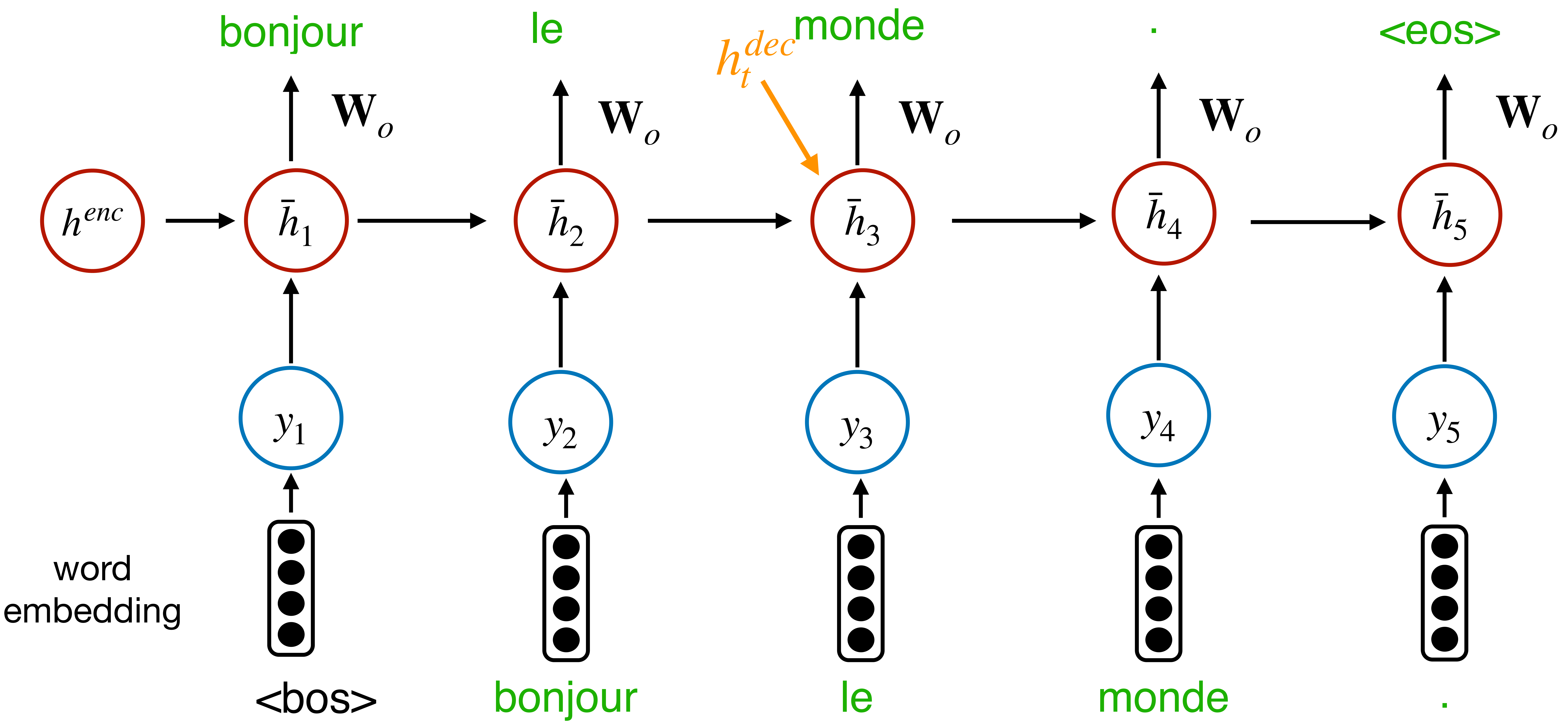
- Attention provides a solution to the bottleneck problem
- **Key idea:** At each time step during decoding, **focus on a particular part** of source sentence
  - This depends on the **decoder's** current hidden state h_t^{dec} (i.e. an idea of what you are trying to decode)
  - Usually implemented as a probability distribution over the hidden states of the **encoder** (h_i^{enc})

Seq2seq: Encoder

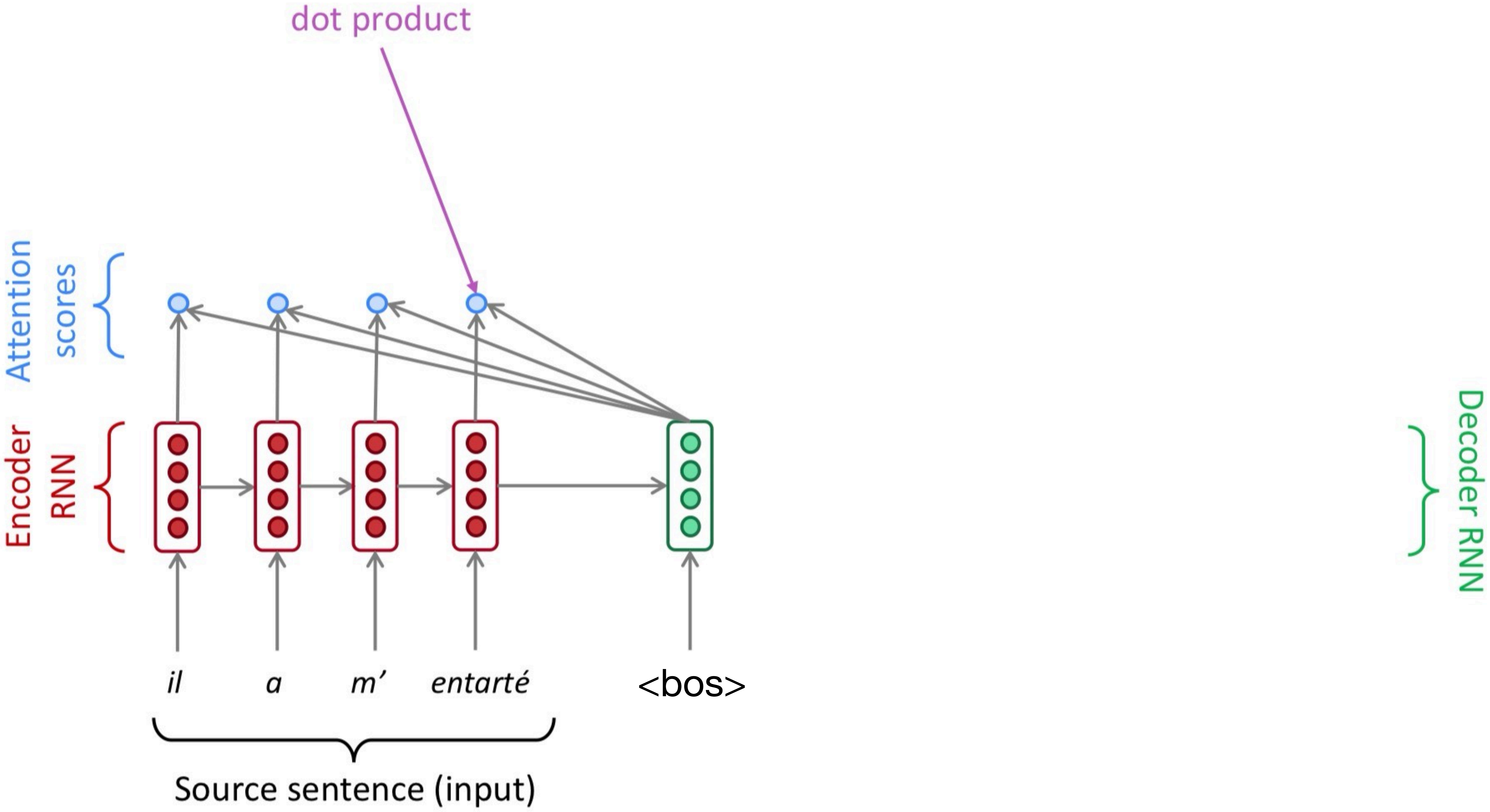


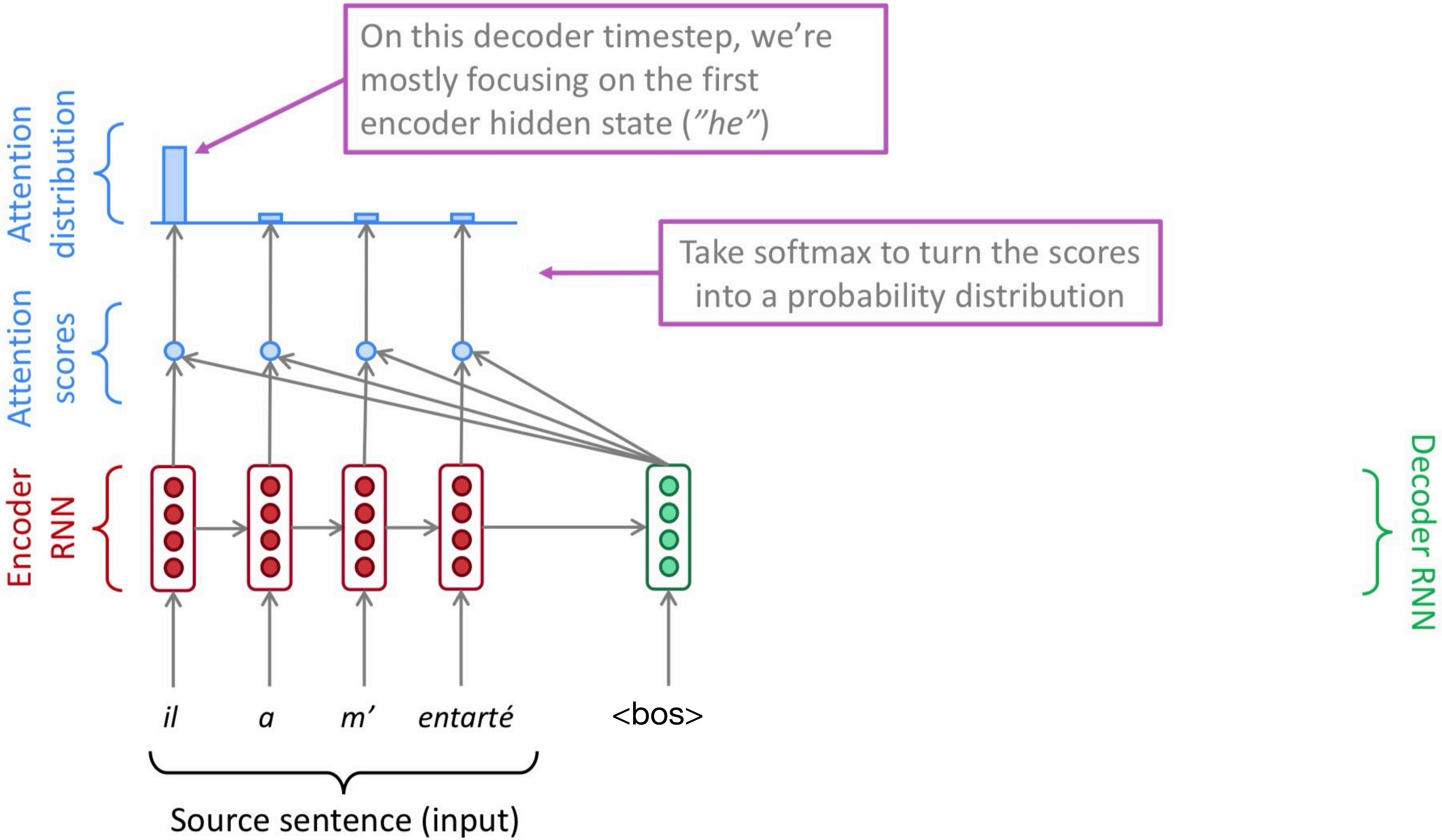
Seq2seq: Decoder

- A **conditional** language model

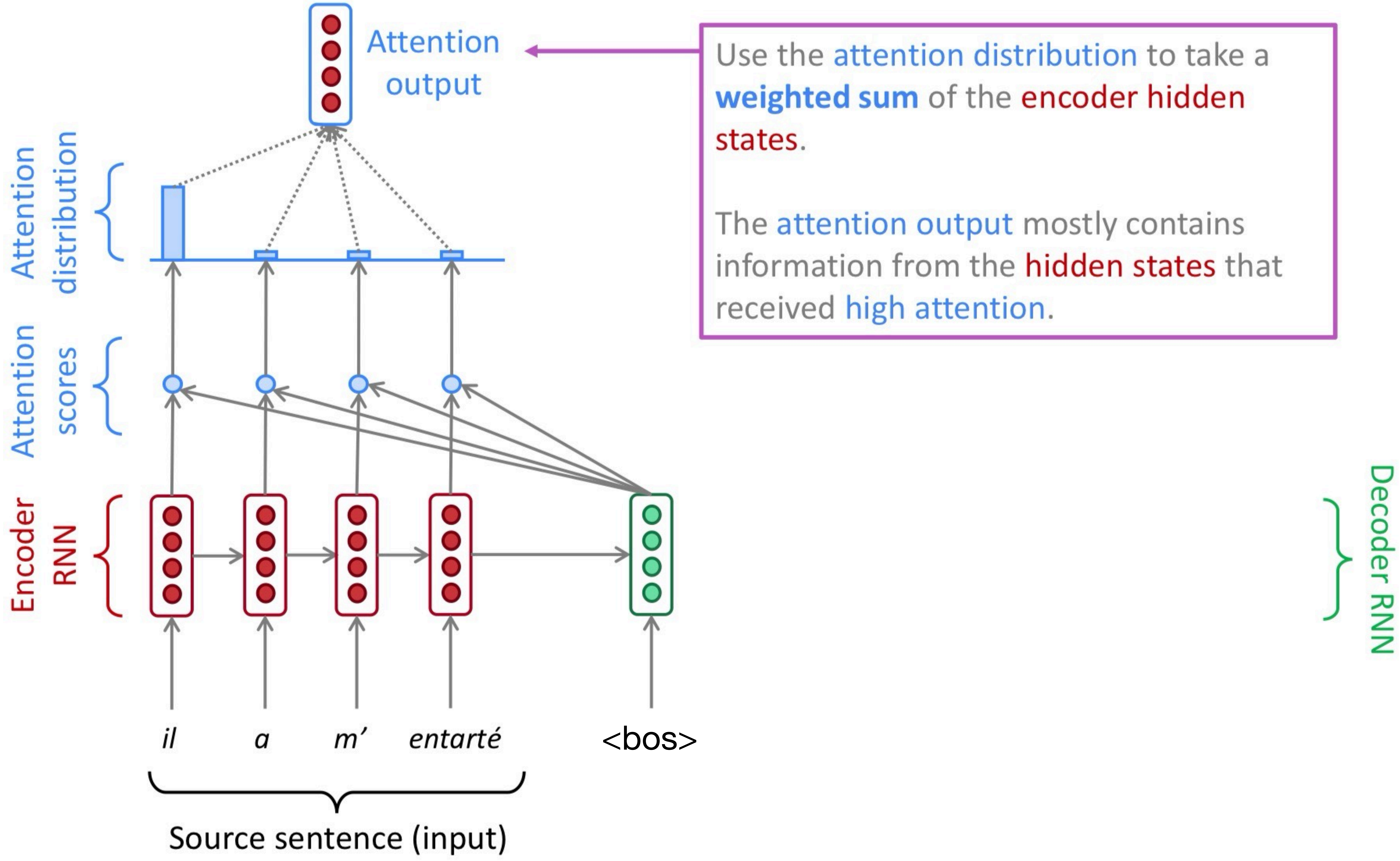


Seq2seq with attention



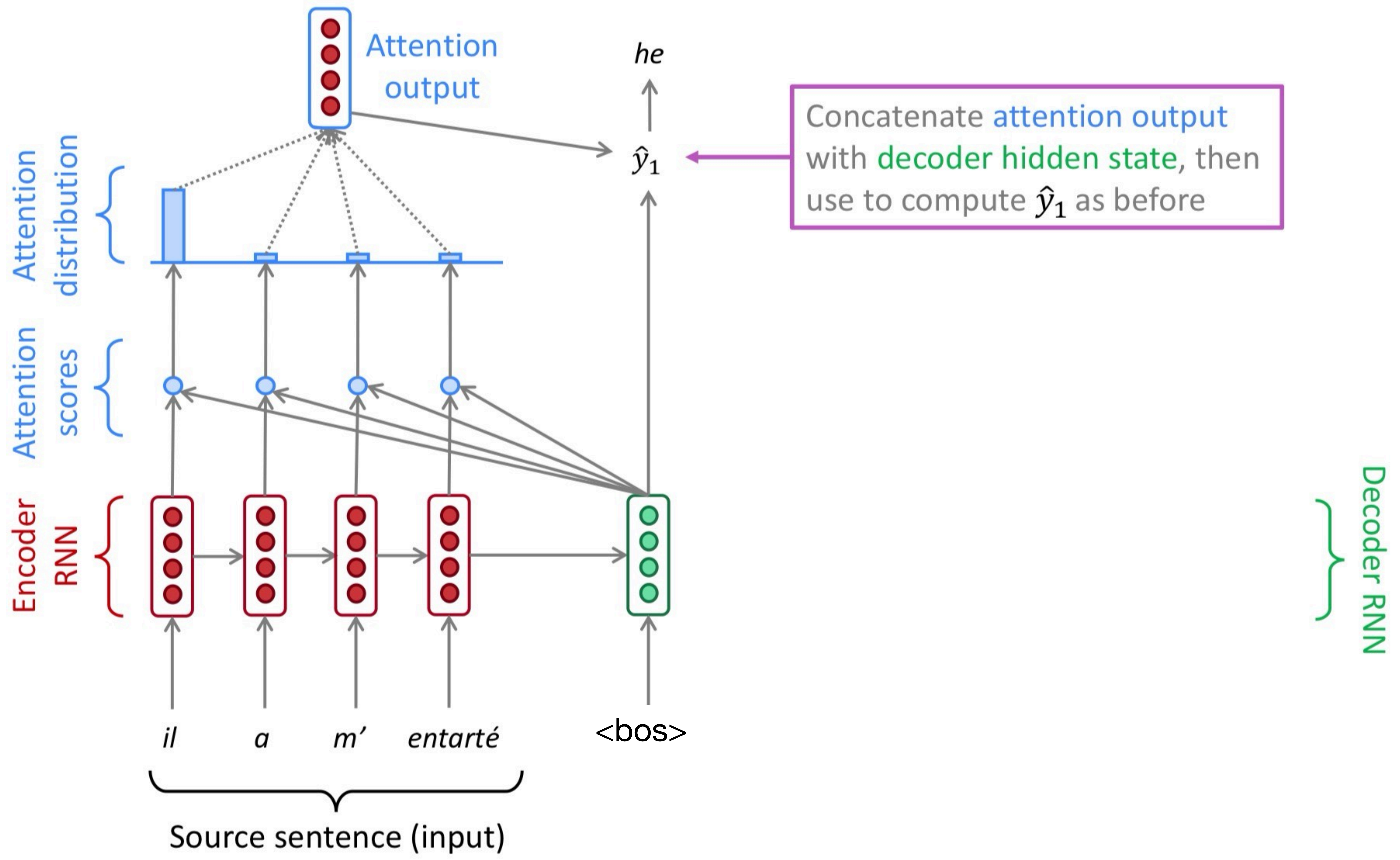


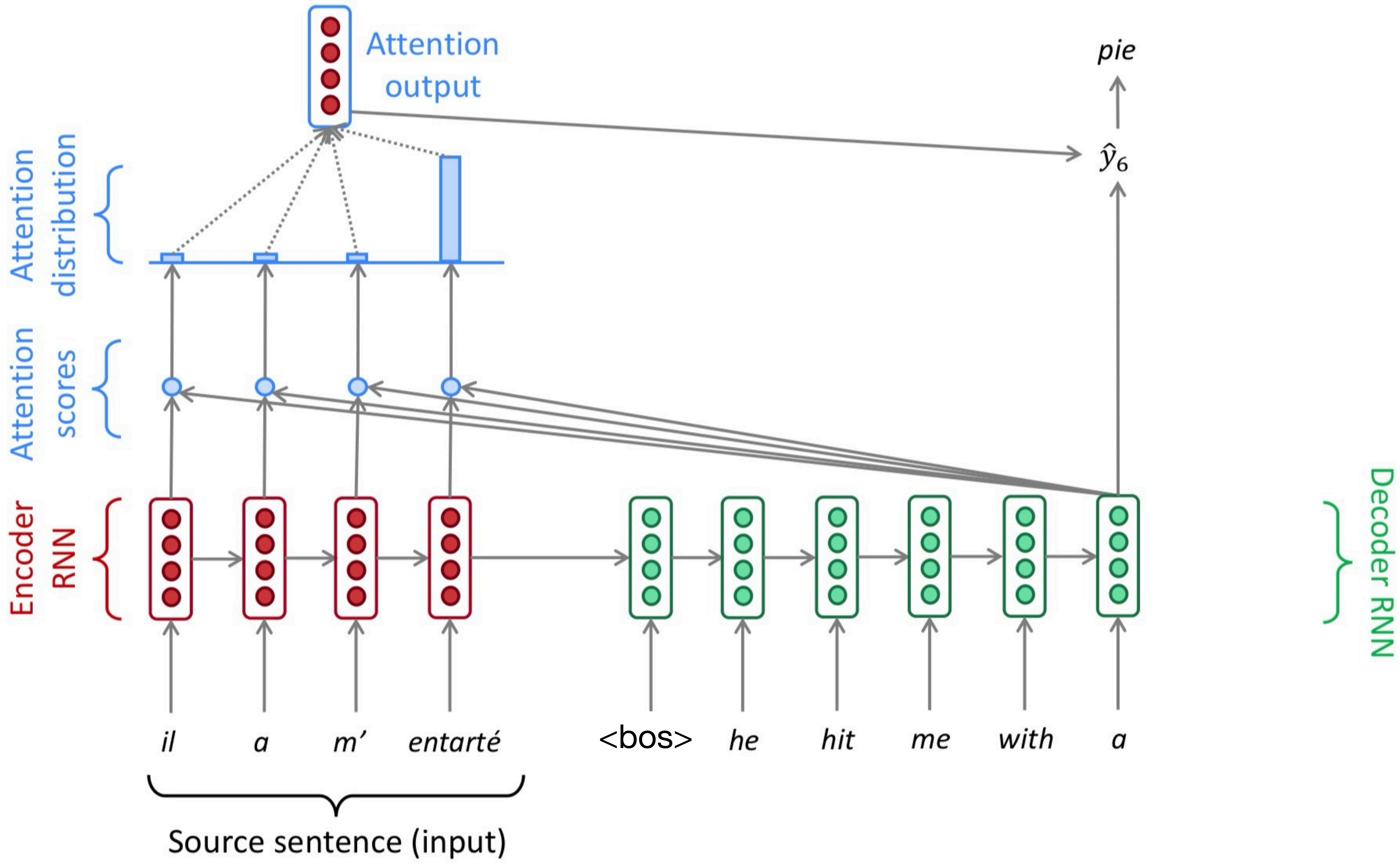
On this decoder timestep, we're mostly focusing on the first encoder hidden state (*"he"*)
Take softmax to turn the scores into a probability distribution
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<bos>
Source sentence (input)



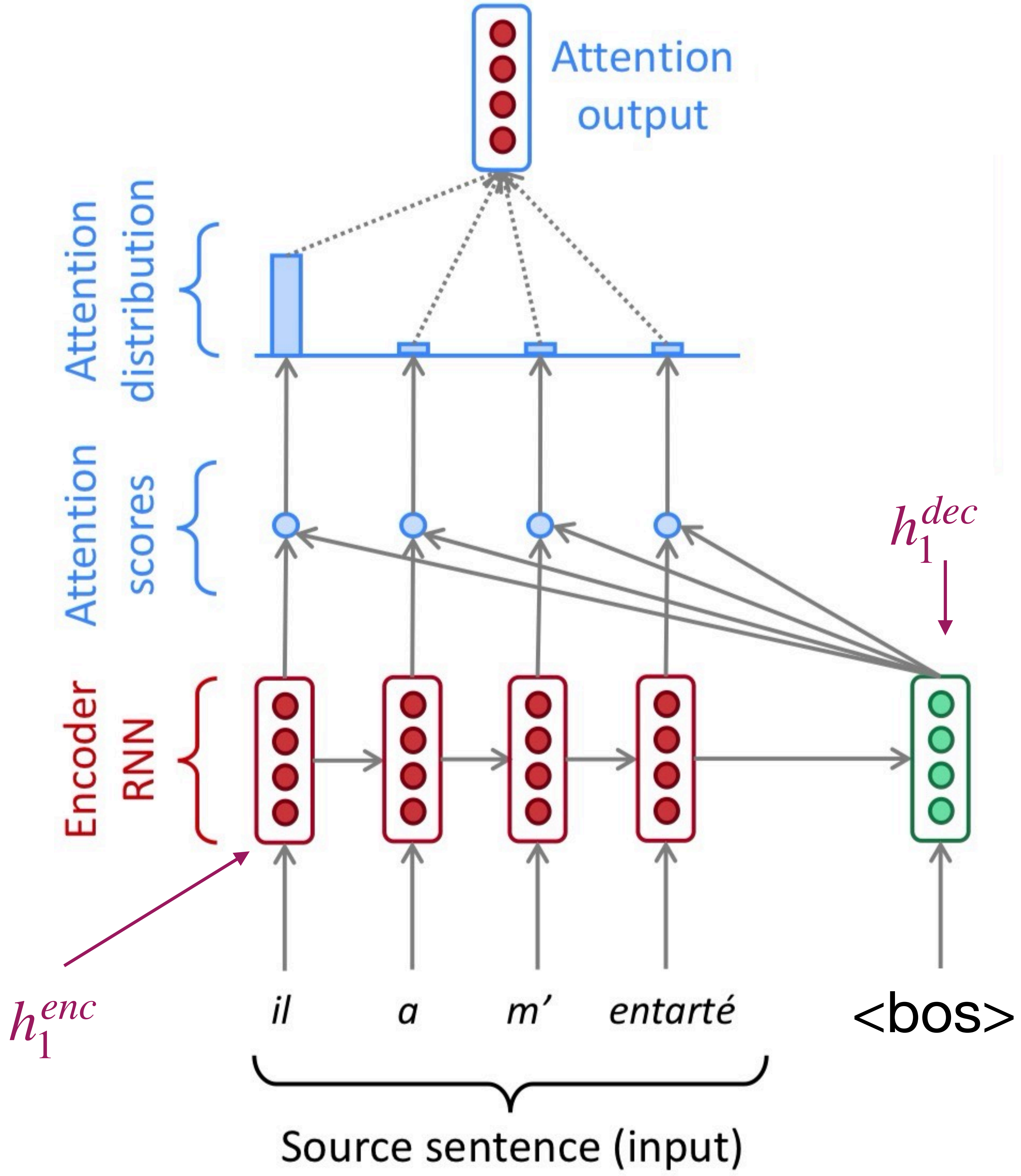
Use the attention distribution to take a **weighted sum** of the encoder hidden states.

The attention output mostly contains information from the hidden states that received high attention.


Attention output
he
$\hat{y}_1$
Concatenate attention output with decoder hidden state, then use to compute $\hat{y}_1$ as before
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<bos>
Source sentence (input)


Attention output
pie
$\hat{y}_6$
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<bos>
he
hit
me
with
a
Source sentence (input)

Computing attention



(n: # of words in source sentence)

- Encoder hidden states: $h_1^{enc}, \ldots, h_n^{enc}$
- Decoder hidden state at time t: h_t^{dec}
- First, get attention scores for this time step of decoder (we'll define g soon):

$$e^t = [g(h_1^{enc}, h_t^{dec}), \ldots, g(h_n^{enc}, h_t^{dec})]$$

- Obtain the attention distribution using softmax:

$$\alpha^t = \text{softmax}\,(e^t) \in \mathbb{R}^n$$

- Compute weighted sum of encoder hidden states:

$$a_t = \sum_{i=1}^{n} \alpha_i^t h_i^{enc} \in \mathbb{R}^h$$

- Finally, concatenate with decoder state and pass on to output layer:

$$\tilde{h}_t = \tanh(\mathbf{W}_c[a_t; h_t^{dec}]) \in \mathbb{R}^h \quad \mathbf{W}_c \in \mathbb{R}^{2h \times h}$$

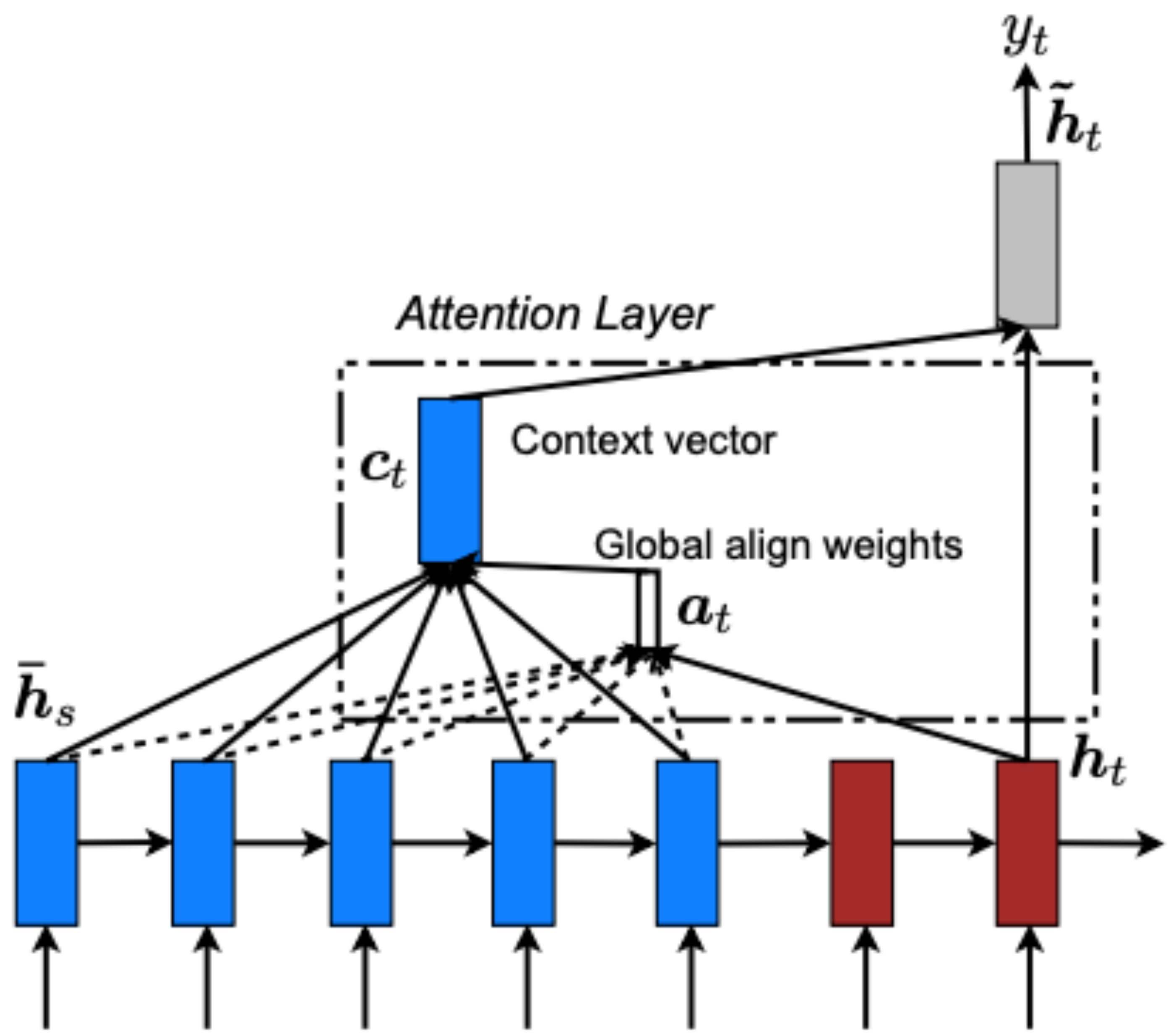
Attention

Published as a conference paper at ICLR 2015

NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

Dzmitry Bahdanau
Jacobs University Bremen, Germany

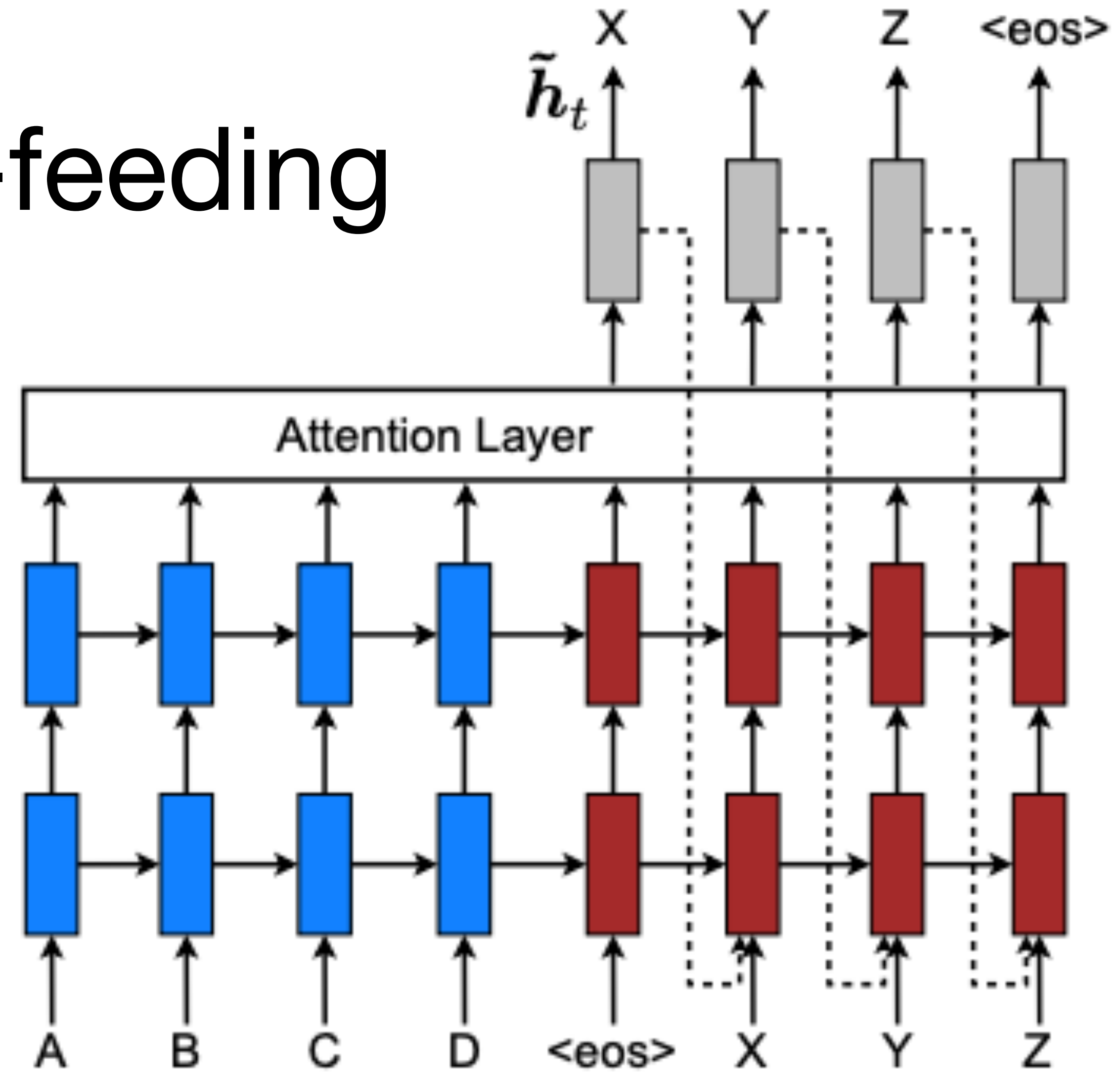
KyungHyun Cho **Yoshua Bengio***
Université de Montréal



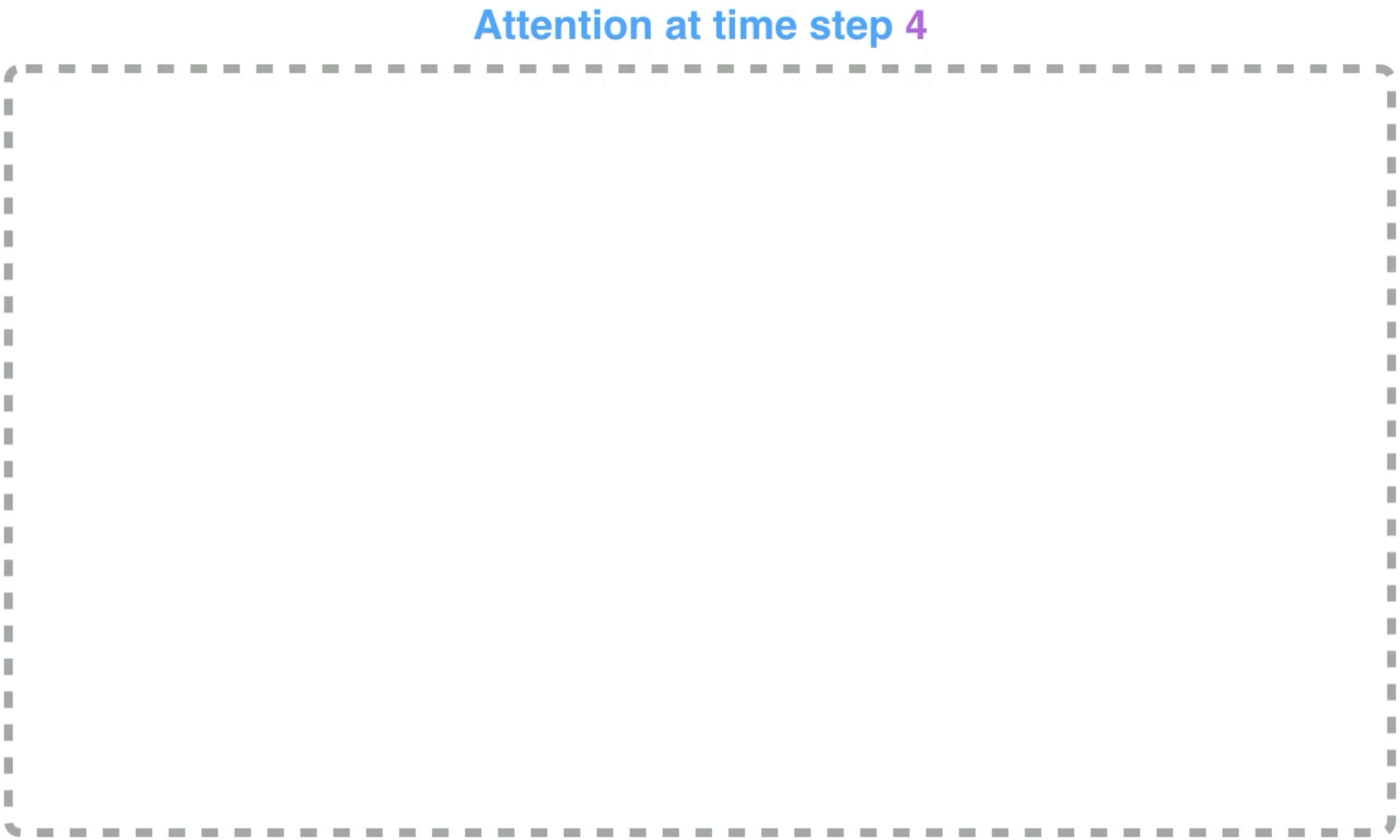
Effective Approaches to Attention-based Neural Machine Translation

Minh-Thang Luong **Hieu Pham** **Christopher D. Manning**
Computer Science Department, Stanford University, Stanford, CA 94305
{lmthang,hyhieu,manning}@stanford.edu

Input-feeding

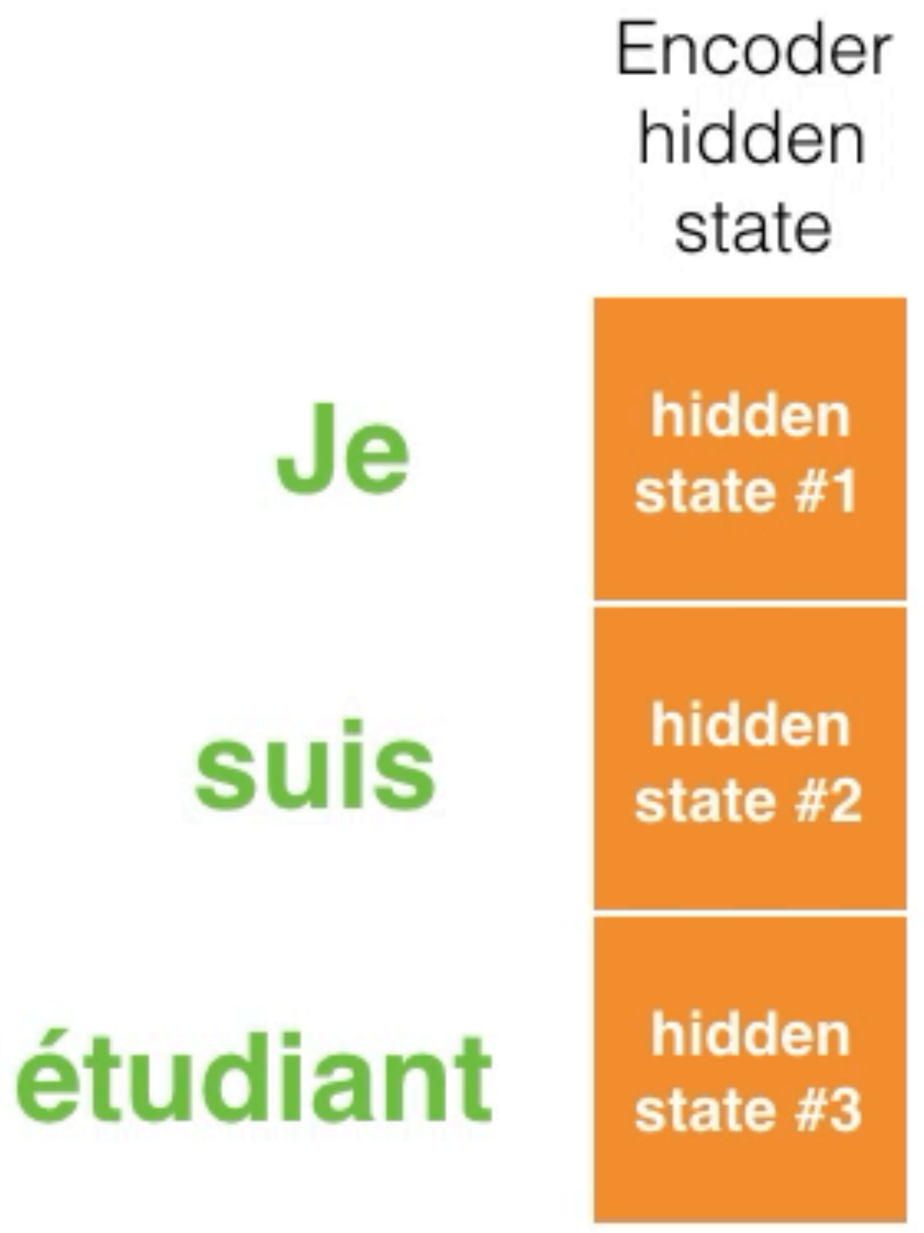


Computing attention



https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

(credits: Jay Alammar)



https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

(credits: Jay Alammar)

Types of attention

- Assume encoder hidden states $h_1^{enc}, h_2^{enc}, \ldots, h_n^{enc}$ and a decoder hidden state h_t^{dec}

1. **Dot-product attention** (assumes equal dimensions for h^{enc} and h_t^{dec}):

$$g(h_i^{enc}, h_t^{dec}) = (h_t^{dec})^T \ h_i^{enc} \in \mathbb{R}$$

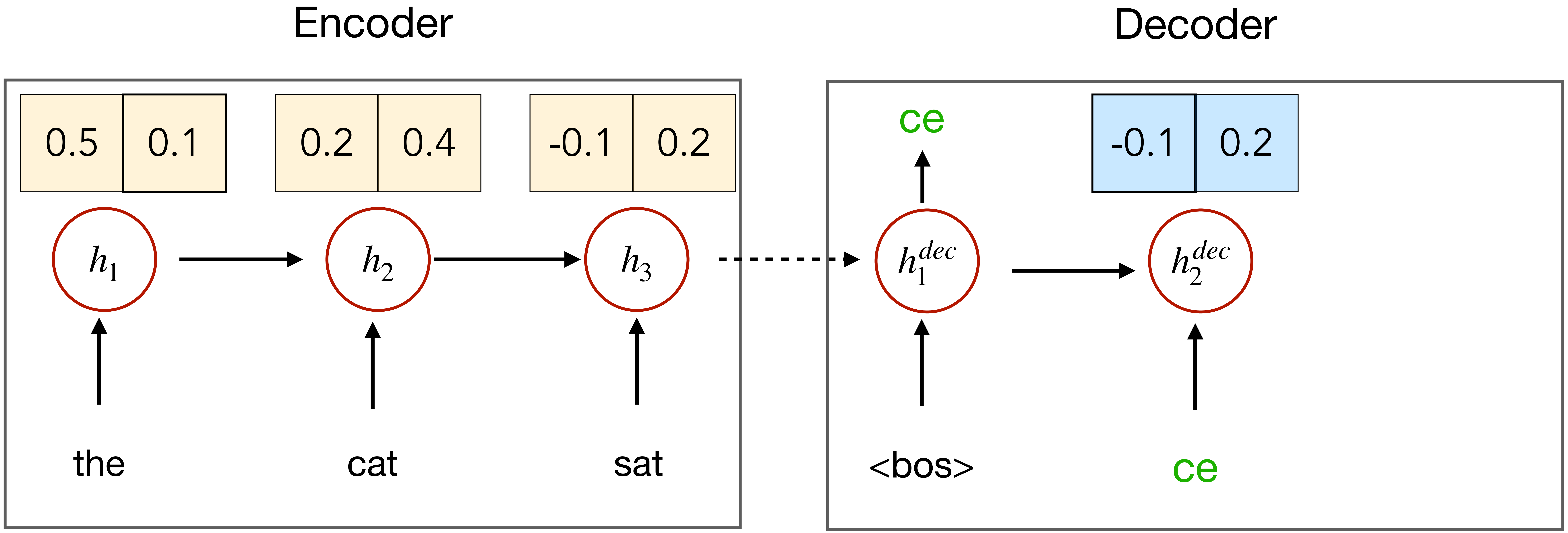
2. **Multiplicative attention:**

$$g(h_i^{enc}, h_t^{dec}) = (h_t^{dec})^T \ W \ h_i^{enc} \in \mathbb{R}$$, where W is a weight matrix (learned)

3. **Additive attention:**

$$g(h_i^{enc}, h_t^{dec}) = v^T \tanh\left(W_1 h_i^{enc} + W_2 h_t^{dec}\right) \in \mathbb{R}$$

where W_1, W_2 are weight matrices (learned) and v is a weight vector (learned)



Dot-product attention:

$$g(h_i^{enc}, h_t^{dec}) = h_t^{dec} \cdot h_i^{enc}$$

Assuming we use dot product attention, which input word will have the highest attention value at current time step?

A) the
B) cat
C) sat

The answer is (B)

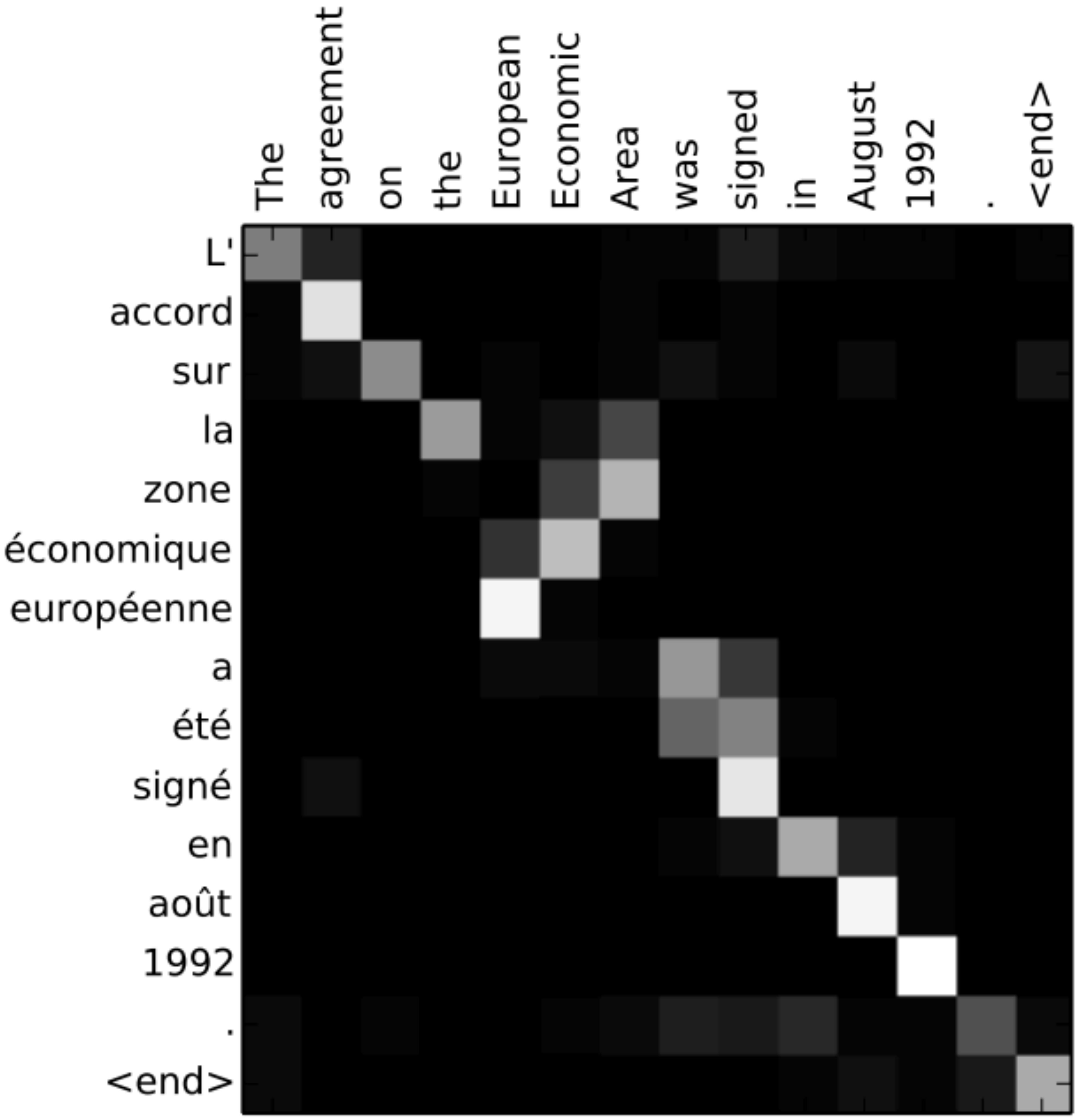
the: -0.05 + 0.02
cat: -0.02 + 0.08
sat: 0.01 + 0.04

Attention improves translation

System	Ppl	BLEU
Winning WMT'14 system – *phrase-based* + *large LM* (Buck et al., 2014)		20.7
Existing NMT systems		
RNNsearch (Jean et al., 2015)		16.5
RNNsearch + unk replace (Jean et al., 2015)		19.0
RNNsearch + unk replace + large vocab + *ensemble* 8 models (Jean et al., 2015)		**21.6**
Our NMT systems		
Base	10.6	11.3
Base + reverse	9.9	12.6 (+*1.3*)
Base + reverse + dropout	8.1	14.0 (+*1.4*)
Base + reverse + dropout + global attention (*location*)	7.3	16.8 (+*2.8*)
Base + reverse + dropout + global attention (*location*) + feed input	6.4	18.1 (+*1.3*)
Base + reverse + dropout + local-p attention (*general*) + feed input	5.9	19.0 (+*0.9*)
Base + reverse + dropout + local-p attention (*general*) + feed input + unk replace		20.9 (+*1.9*)
Ensemble 8 models + unk replace		**23.0** (+*2.1*)

(Luong et al., 2015)

Visualizing attention



(credits: Jay Alammar)