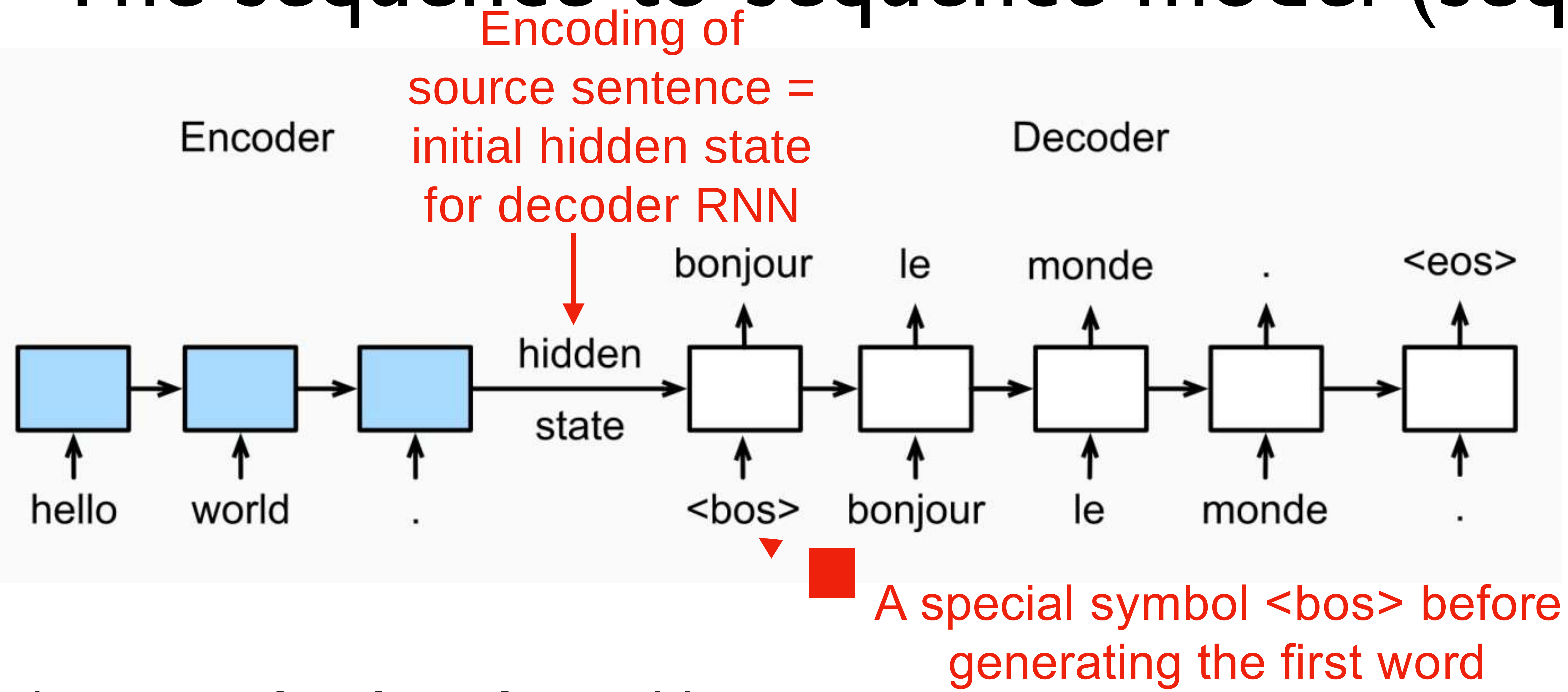
AIE1007: Natural Language Processing

L12: Seq2seq models + attention

Autumn 2024

The sequence-to-sequence model (seq2seq)



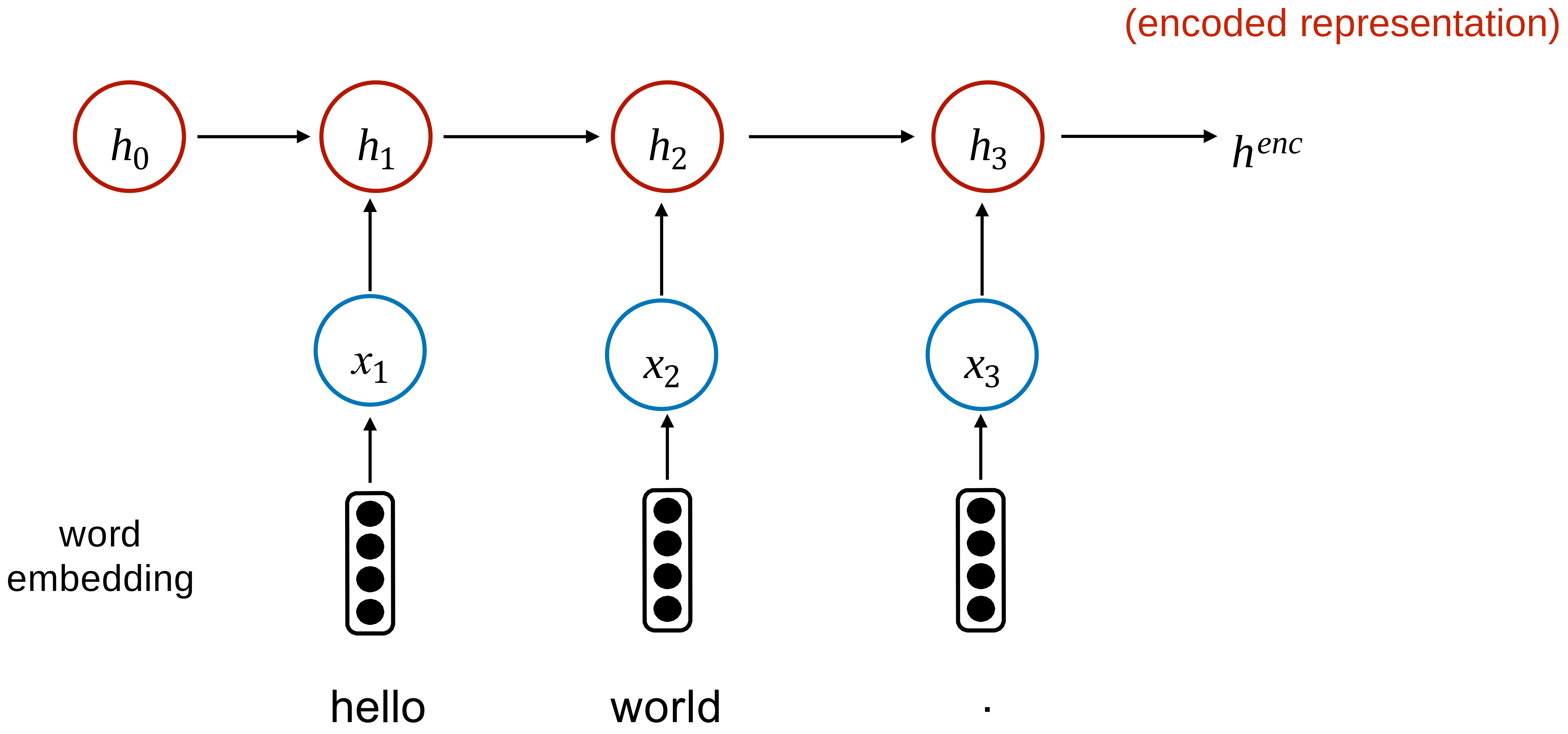
It is called an **encoder-decoder** architecture

- 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

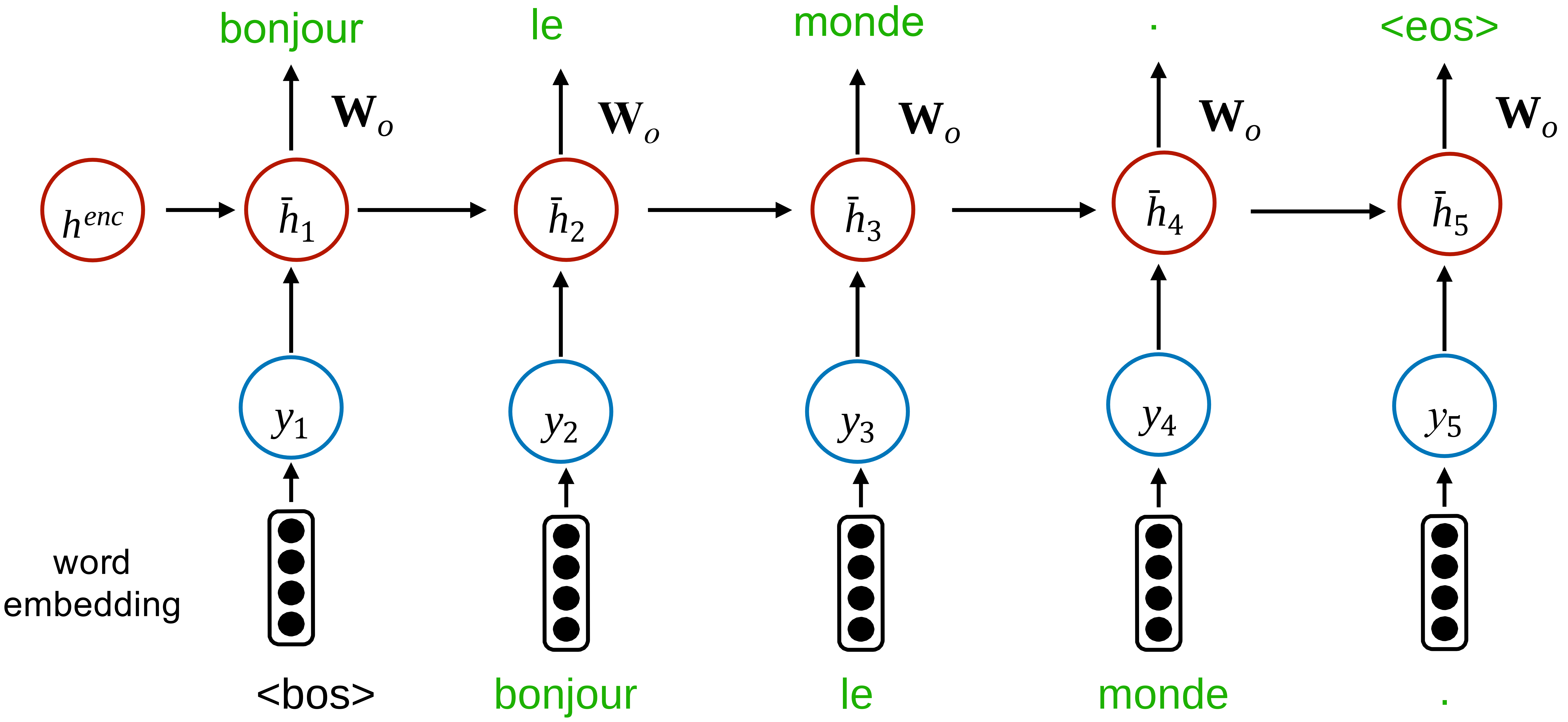
Seq2seq: Encoder

Sentence: hello world .



Seq2seq: Decoder

- A **conditional** language model

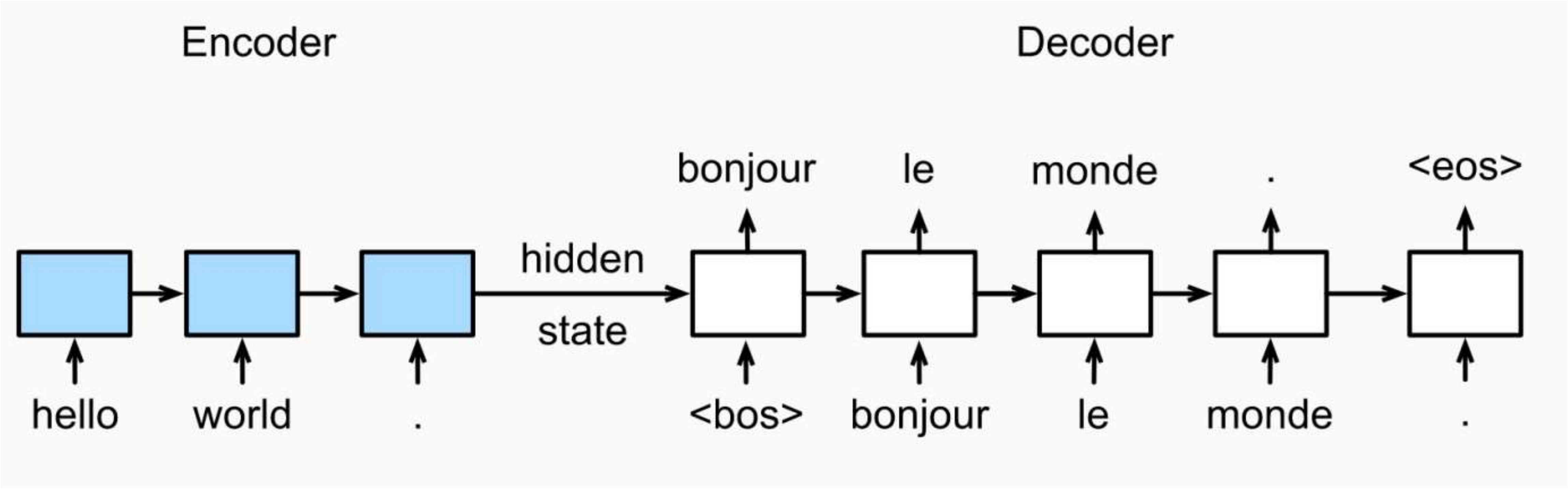


Seq2seq: Decoder

- 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

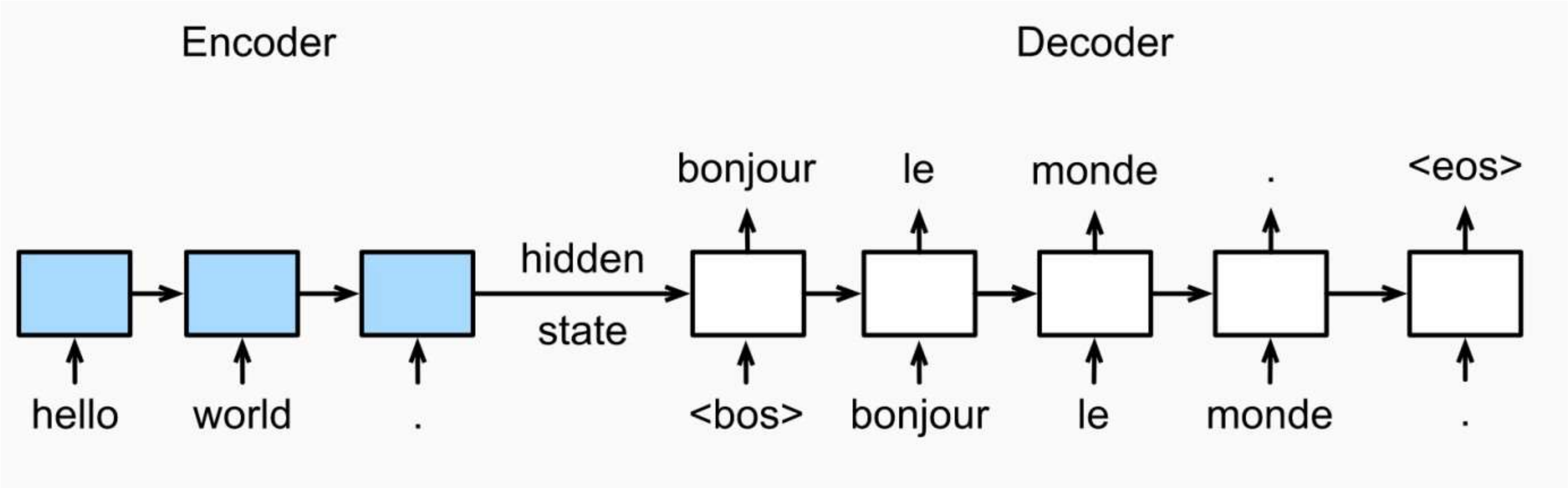


Which of the following is correct?

- (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:

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

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

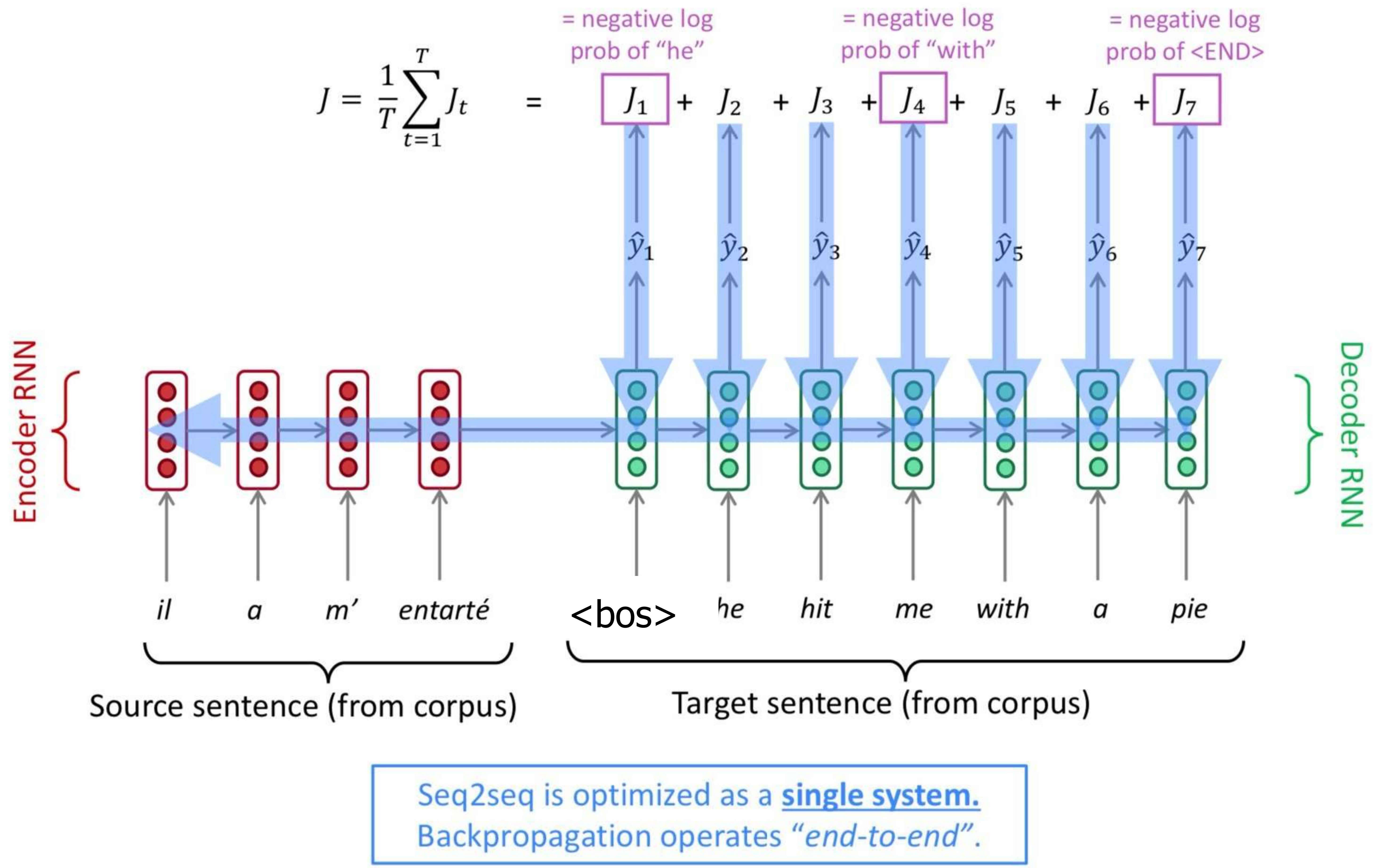
- Back-propagate gradients through both encoder and decoder

12M sentence pairs

French: bonjour le monde .

English: hello world .

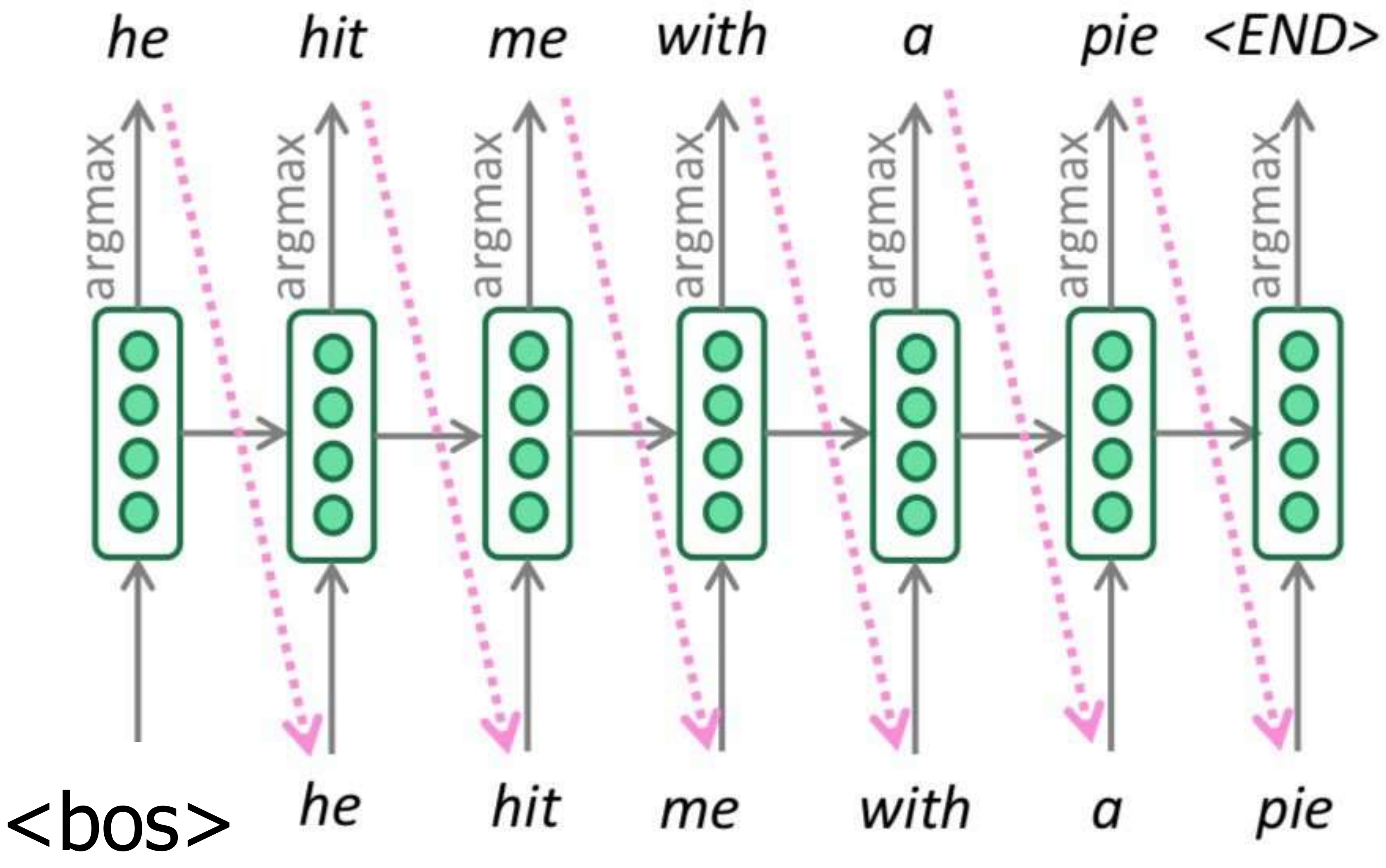
Training seq2seq models



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

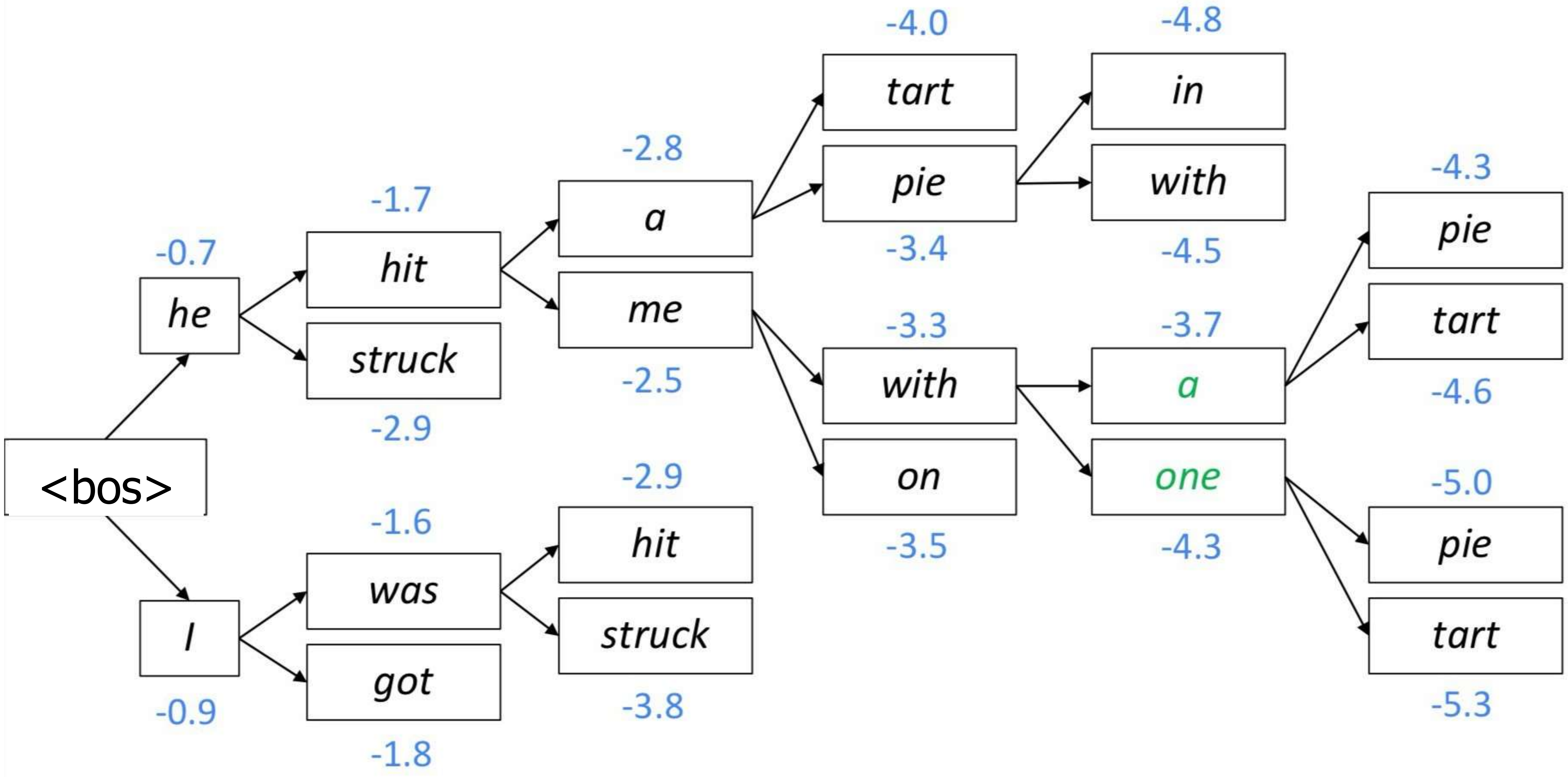
- At every step, keep track of the k most probable partial translations (hypotheses)
- Score of each hypothesis = log probability of sequence so far

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

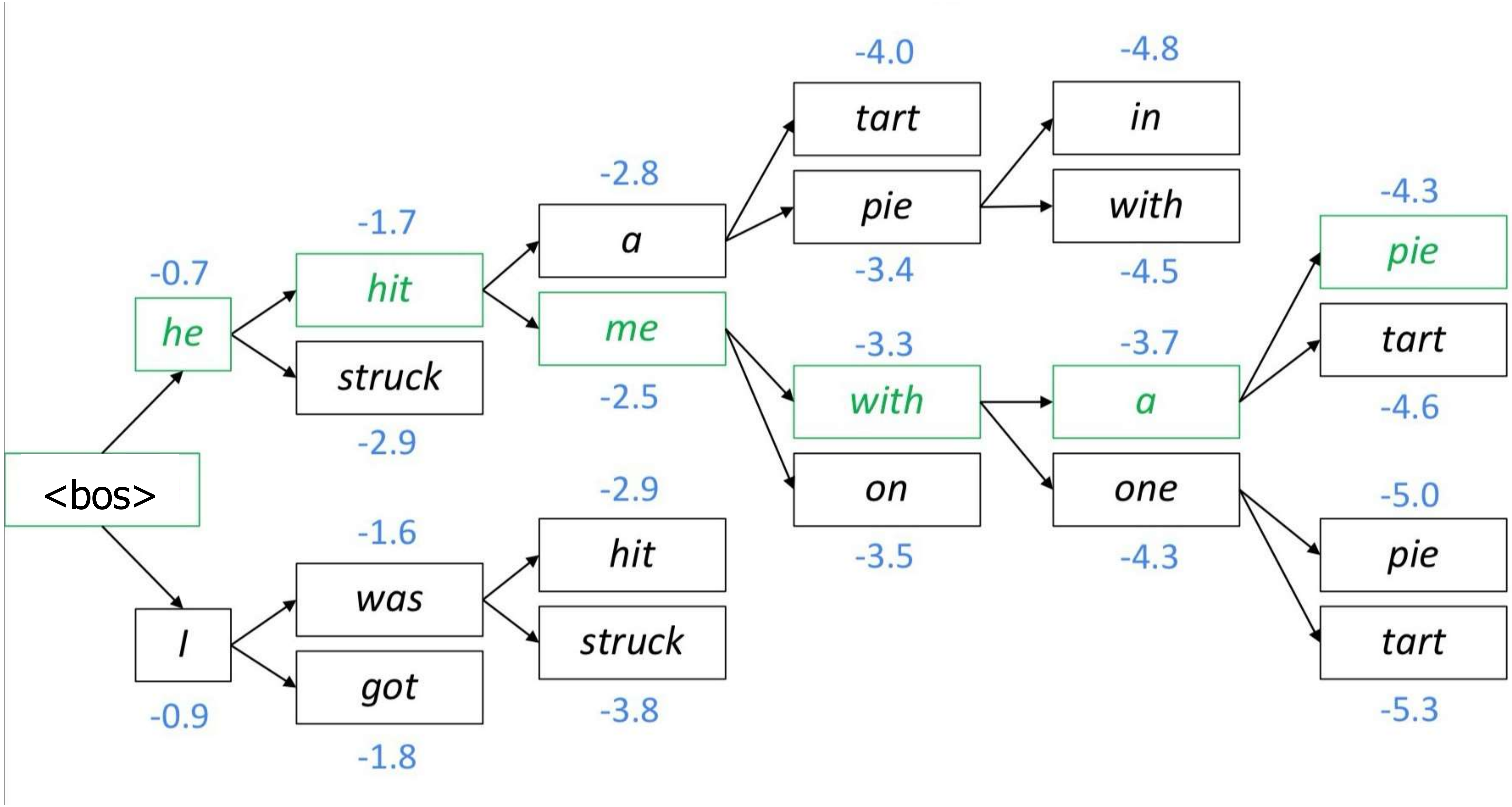
- Not guaranteed to be optimal
- Works better than greedy decoding in practice

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

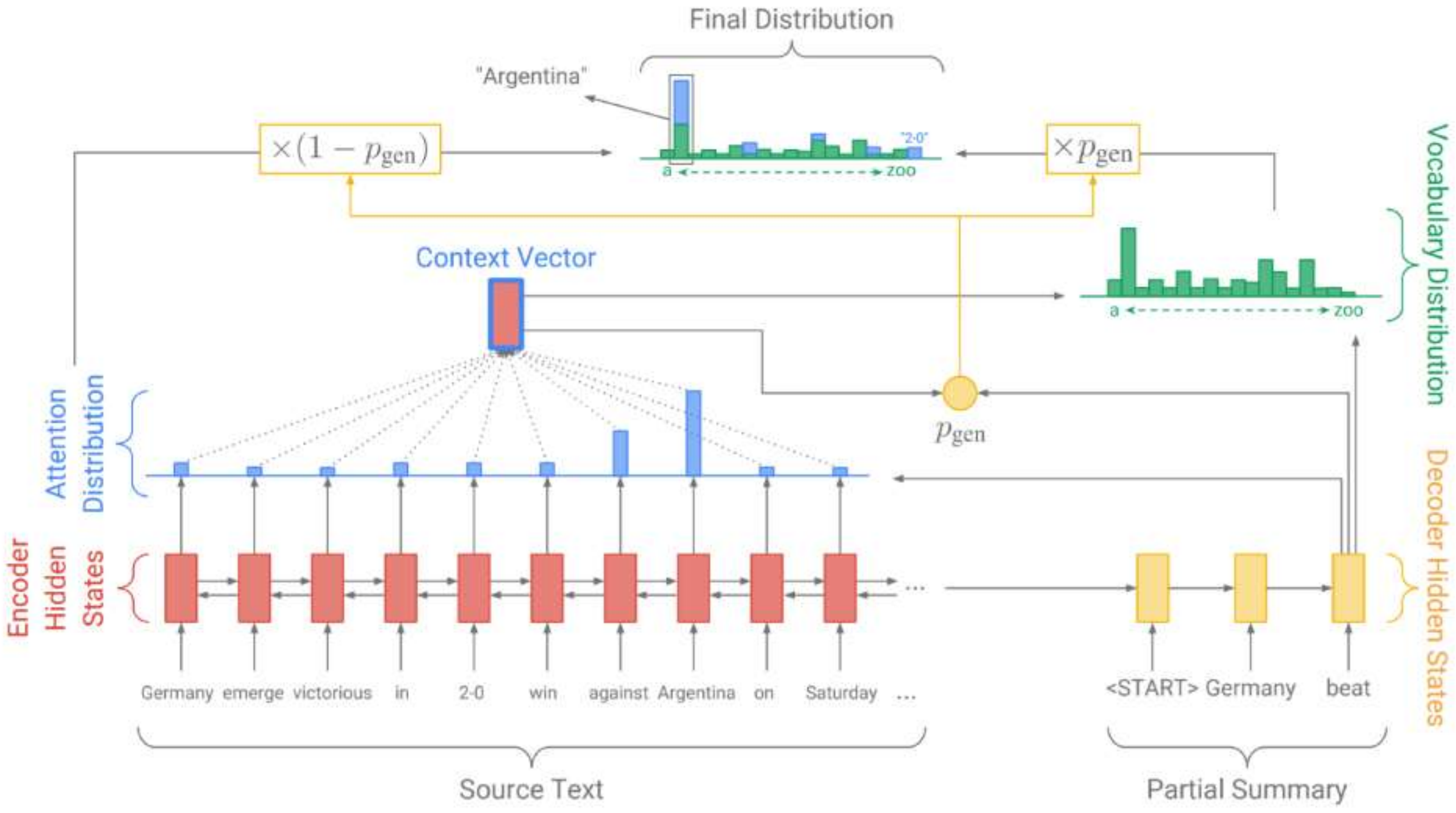
- 2014: First seq2seq paper published
- 2016: Google Translate switches from SMT to NMT - and by 2018 everyone has
- SMT systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a small group of engineers in a few months

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 .

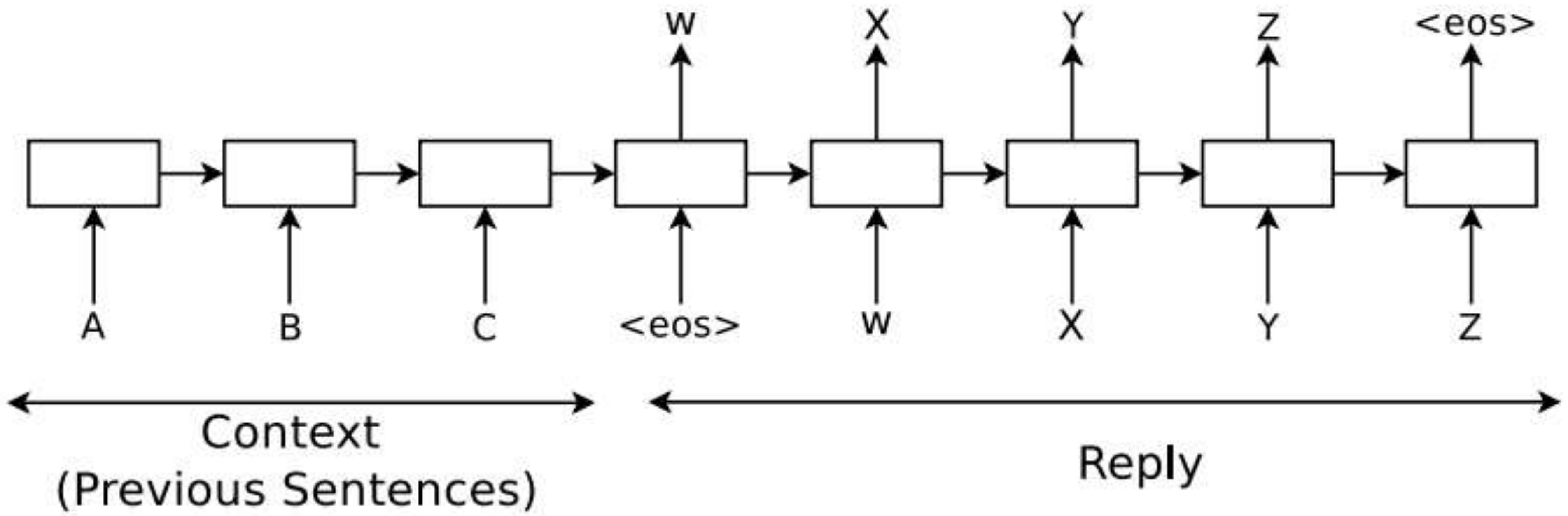
Pointer-generator summary

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

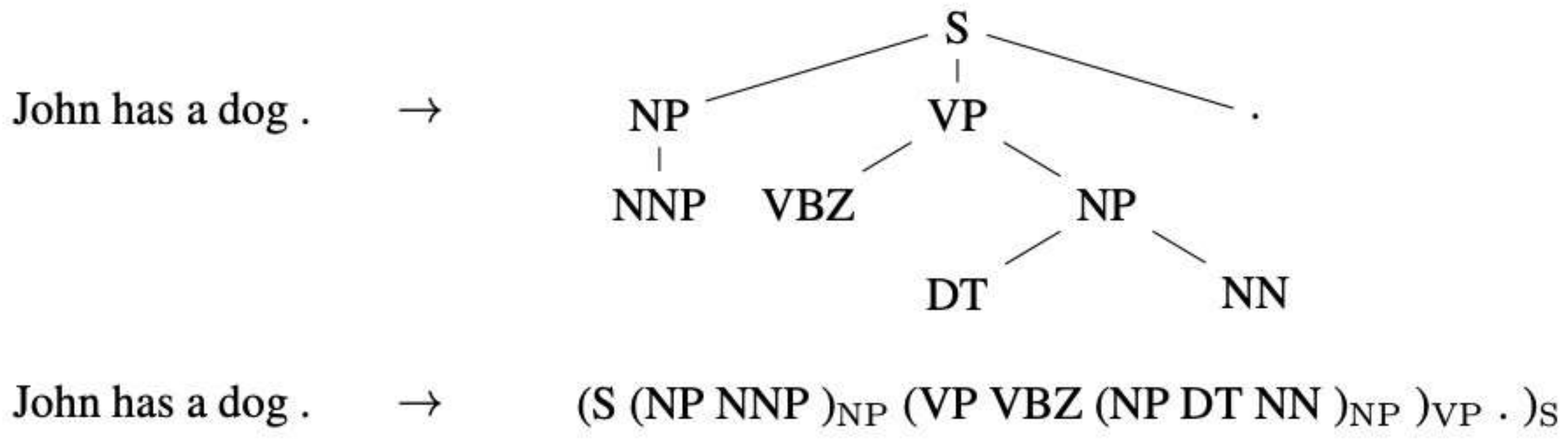


Human: *hello !*
Machine: *hello !*
Human: *how are you ?*
Machine: *i 'm good .*
Human: *what 's your name ?*
Machine: *i 'm julia .*
Human: *when were you born ?*
Machine: *july 20th .*
Human: *what year were you born ?*
Machine: *1977 .*
Human: *where are you from ?*

Vinyals and Le 2015: A Neuarl Conversational Model

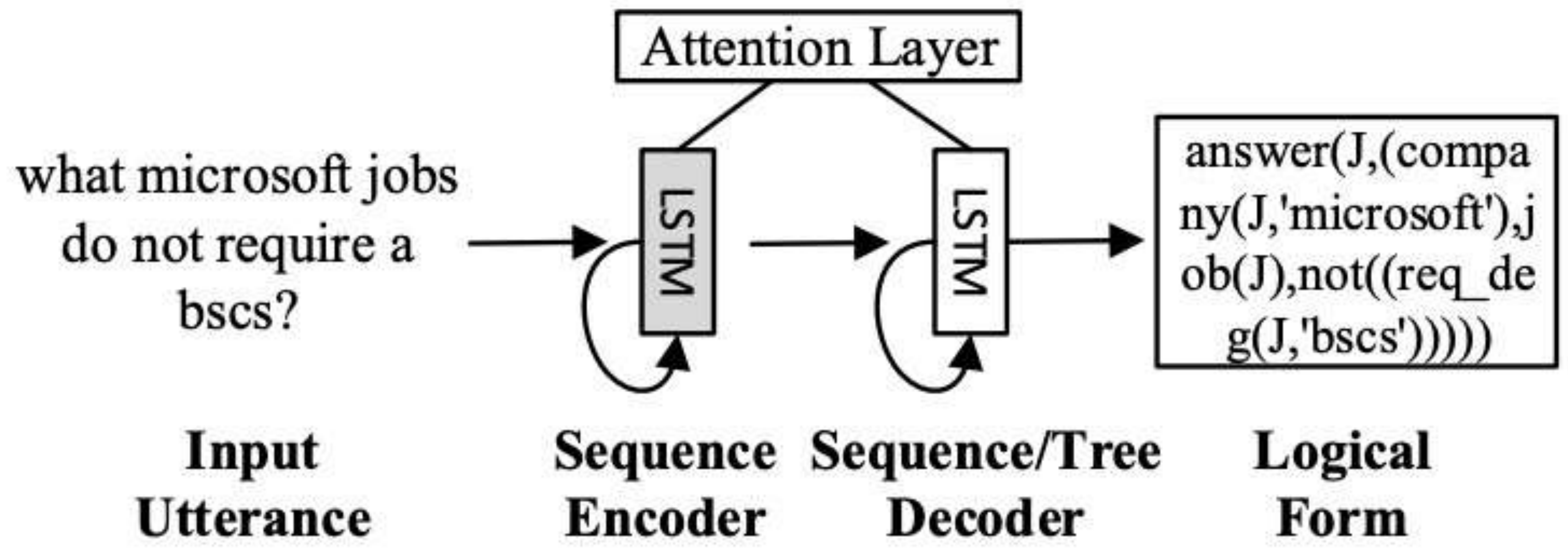
Sequence-to-sequence is versatile

- Parsing



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

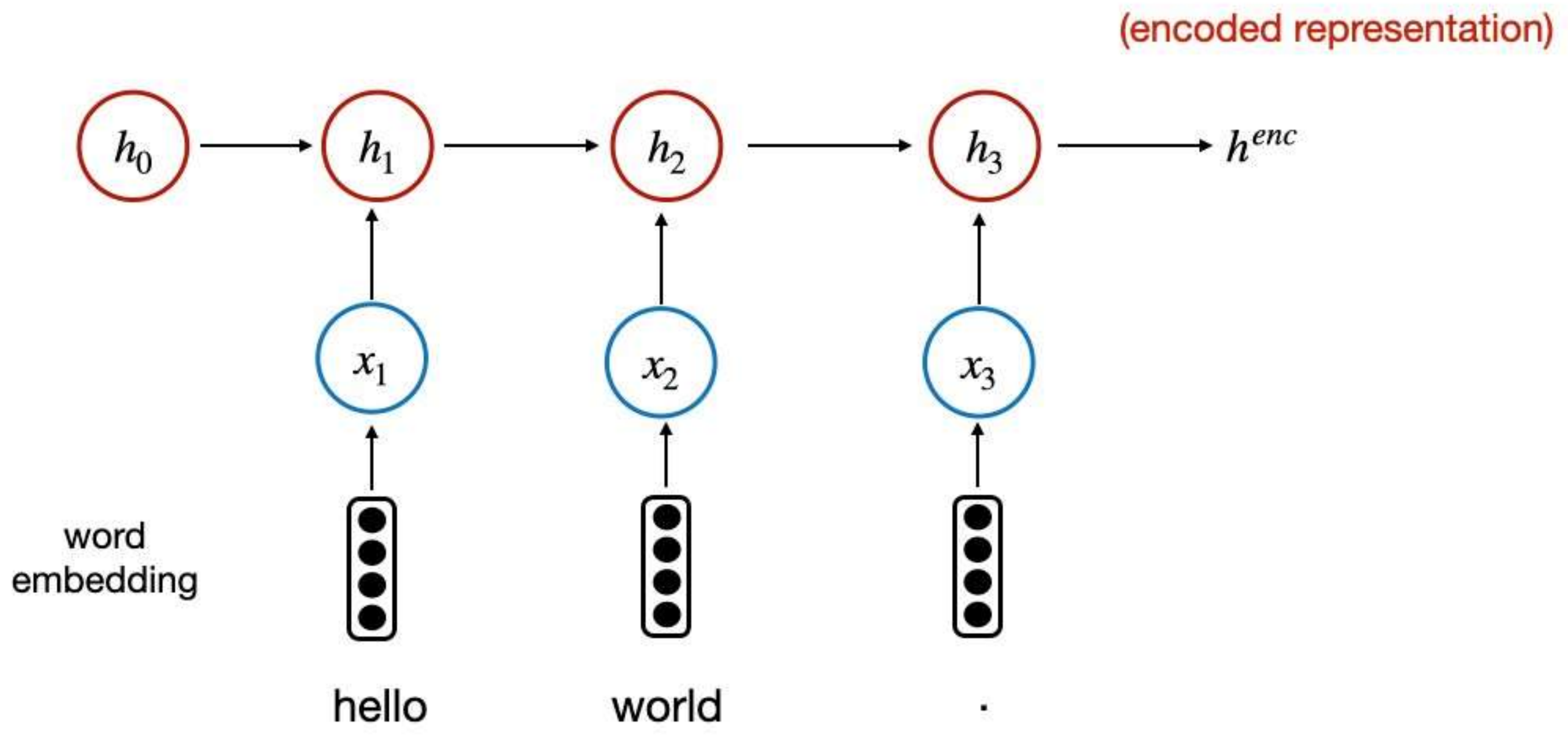
- Semantic parsing / code generation



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)
  $V \leftarrow$ all unique characters in D
    (about 4,000 in English Wikipedia)
  while $|V| < k$ **do** ▷ Merge tokens
    $t_L, t_R \leftarrow$ Most frequent bigram in D
    $t_{\text{NEW}} \leftarrow t_L + t_R$ ▷ Make new token
    $V \leftarrow V + [t_{\text{NEW}}]$
    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:

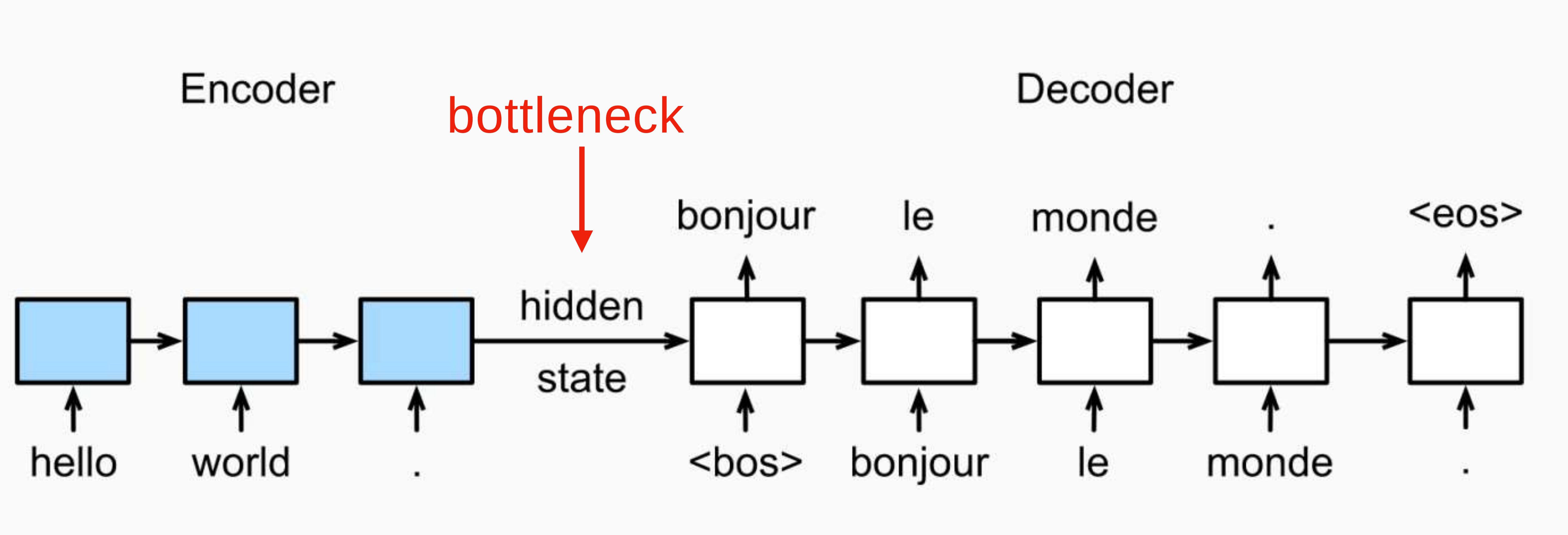
word	count
c a t	4
m a t	5
m a t s	2
m a t e	3
a t e	3
e a t	2

Current merge table:

(empty)

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

Sequence-to-sequence: the bottleneck

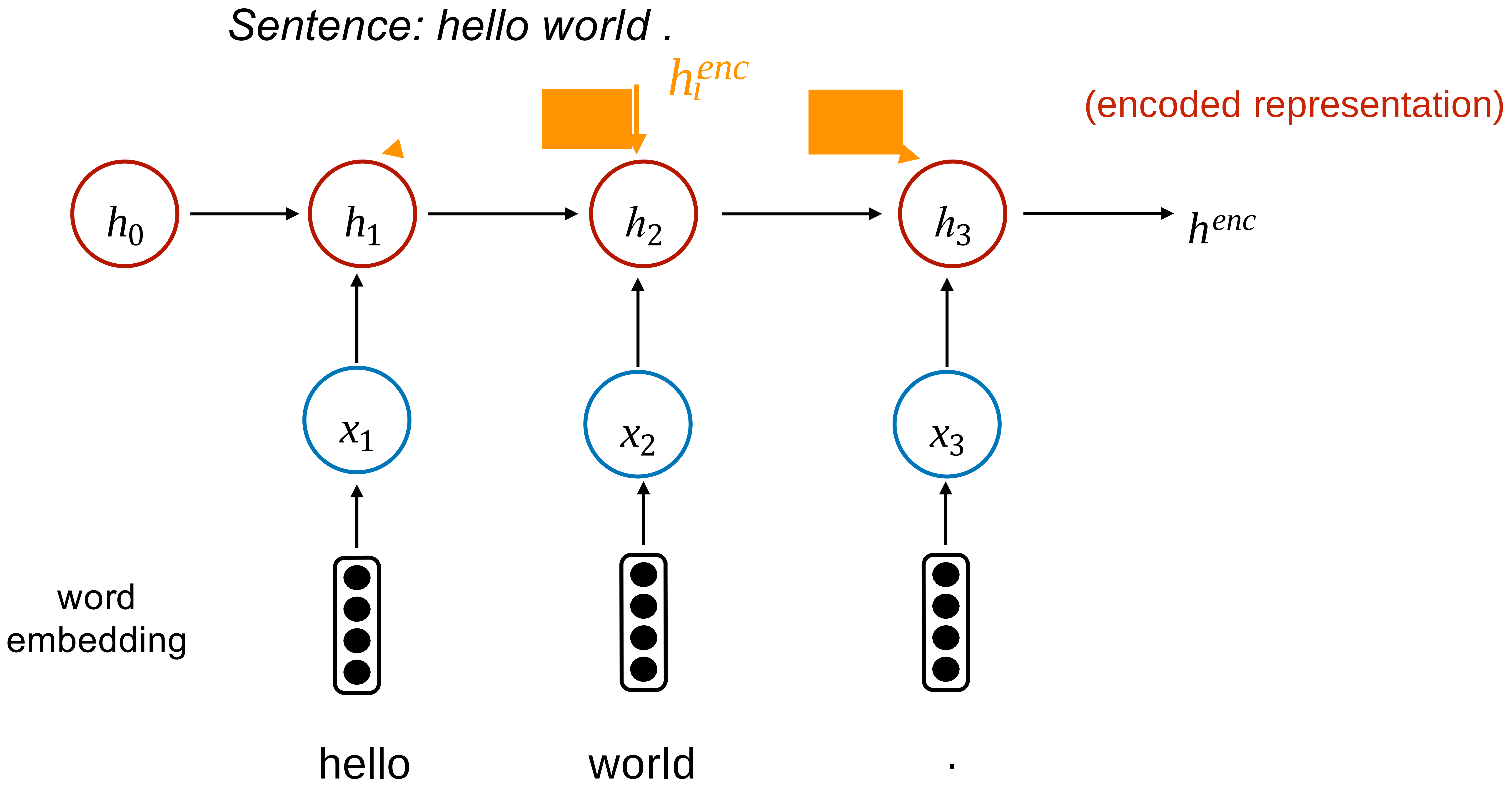


- A single encoding vector, h^{enc}, needs to capture all the information about source sentence
- Longer sequences can lead to vanishing gradients

Attention

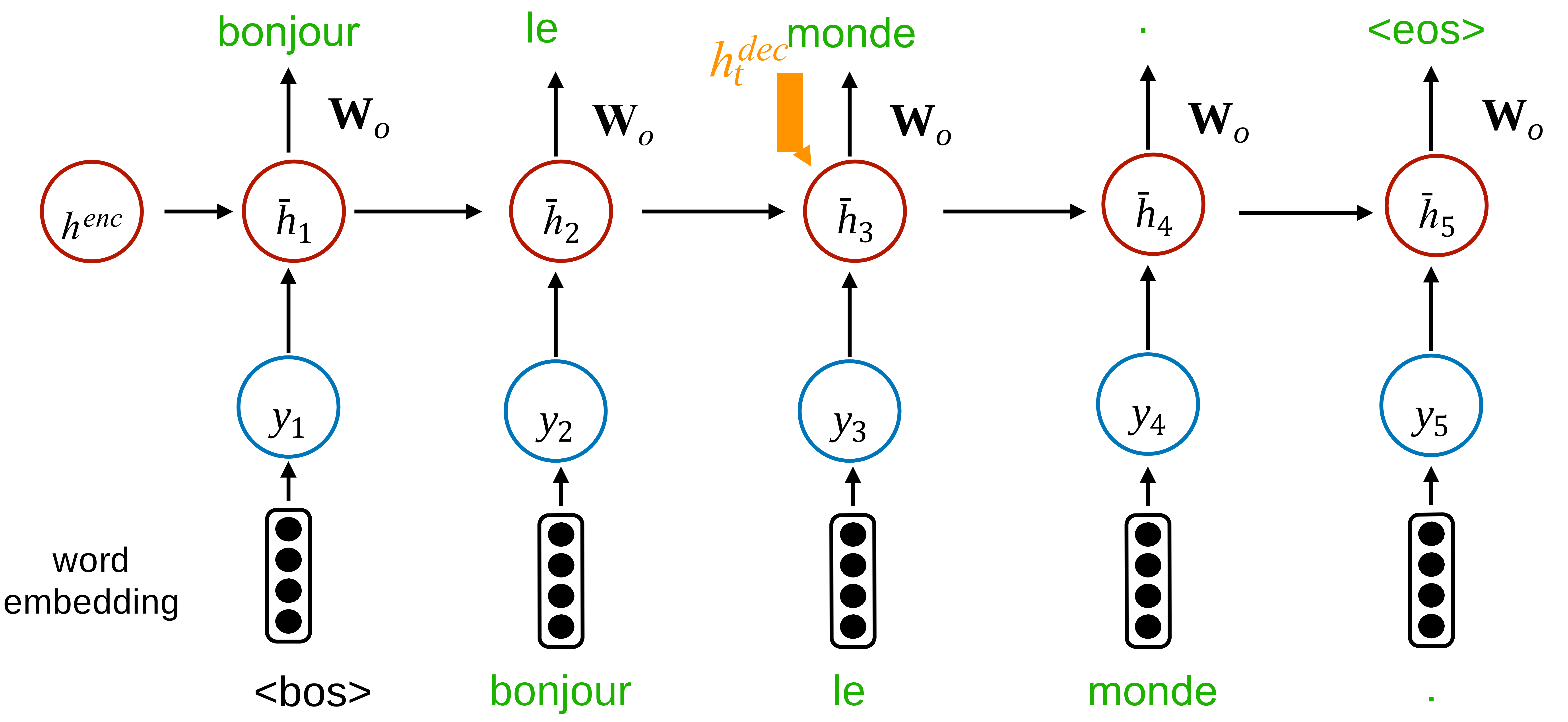
- Attention provides a solution to the bottleneck problem
- **Key idea:** At each time step during decoding, **focus on a particular part** of source sentence
  - This depends on the **decoder's** current hidden state h_t^{dec} (i.e. an idea of what you are trying to decode)
  - Usually implemented as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

Seq2seq: Encoder

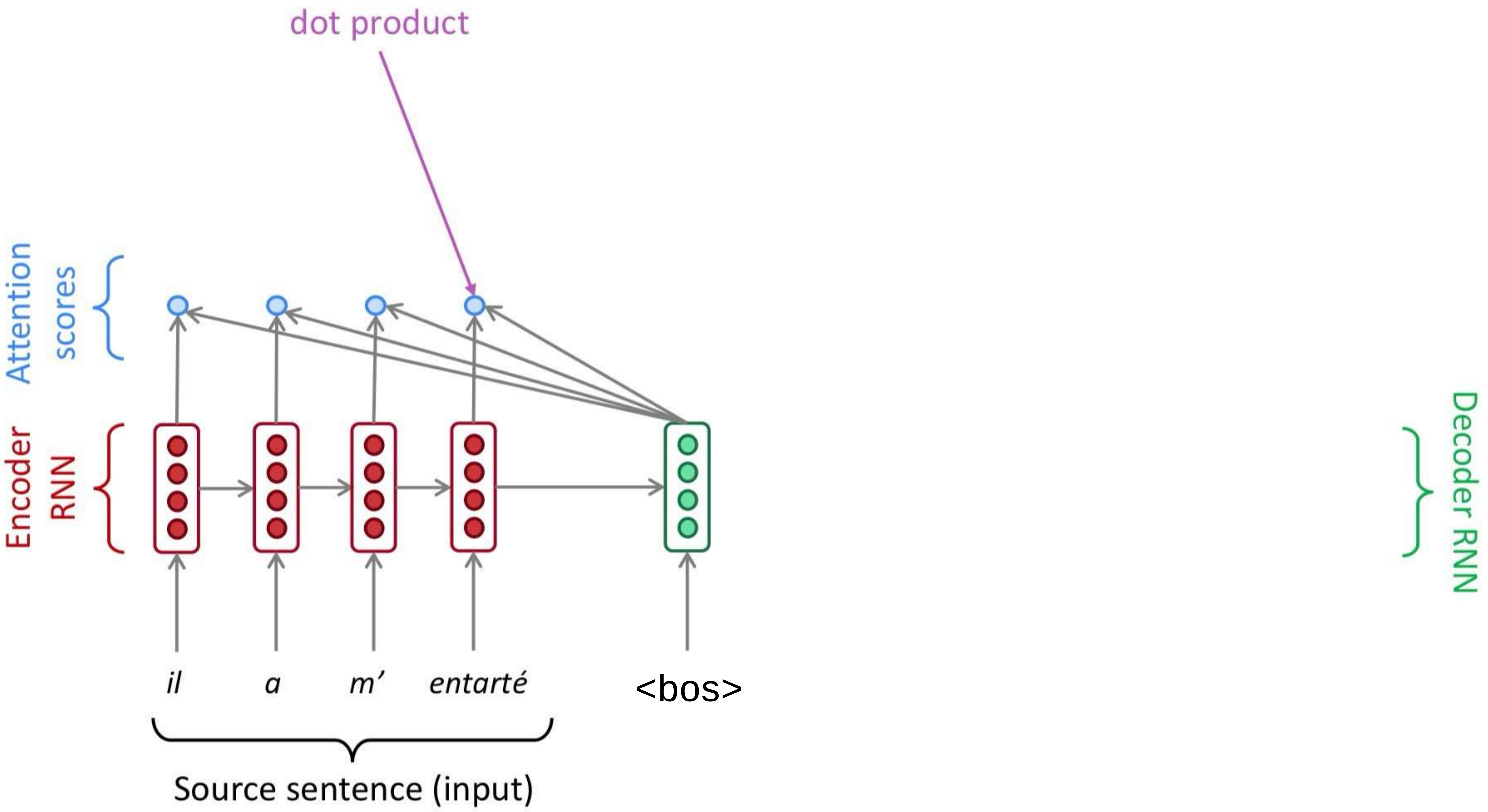


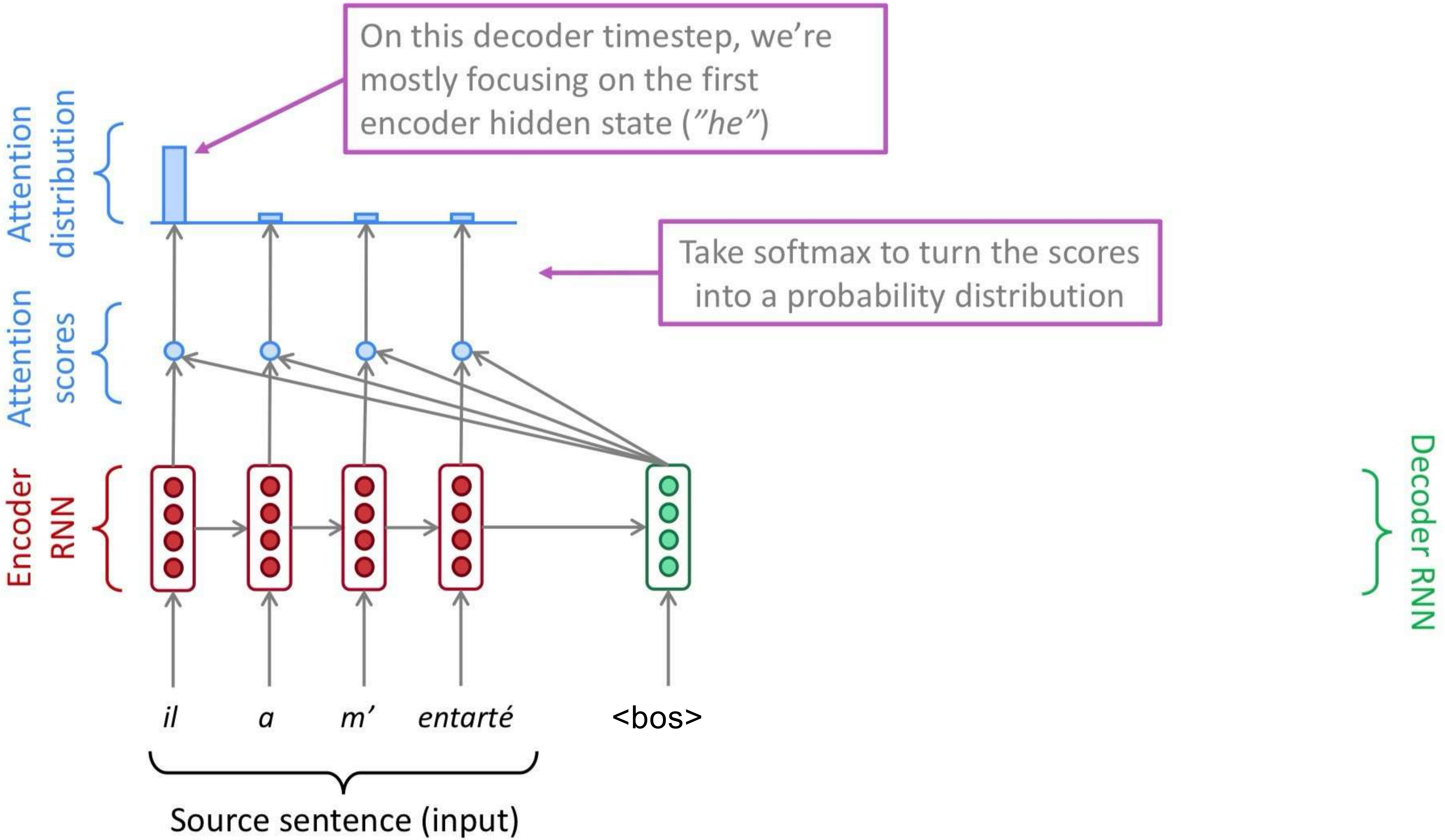
Seq2seq: Decoder

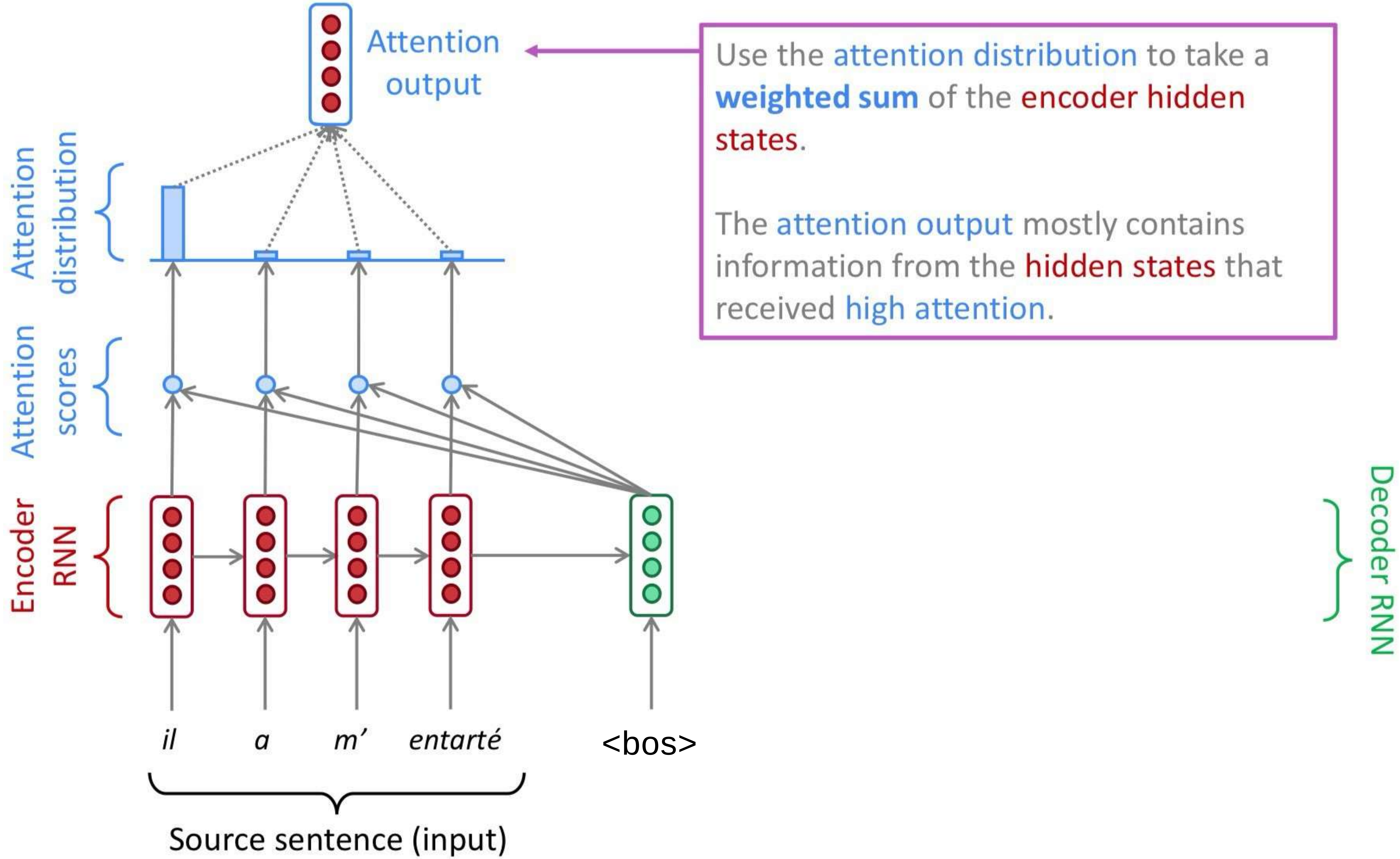
- A **conditional** language model

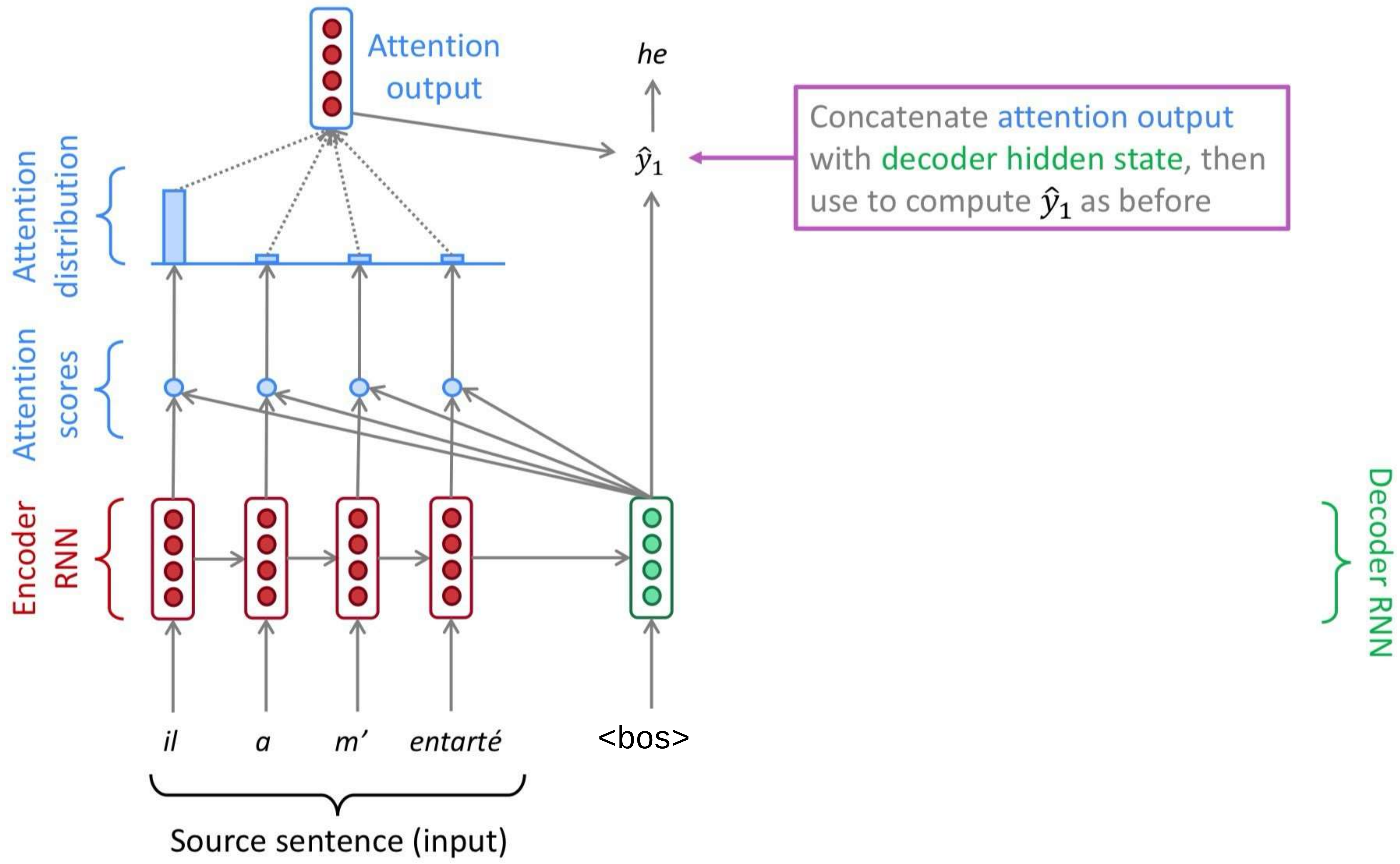


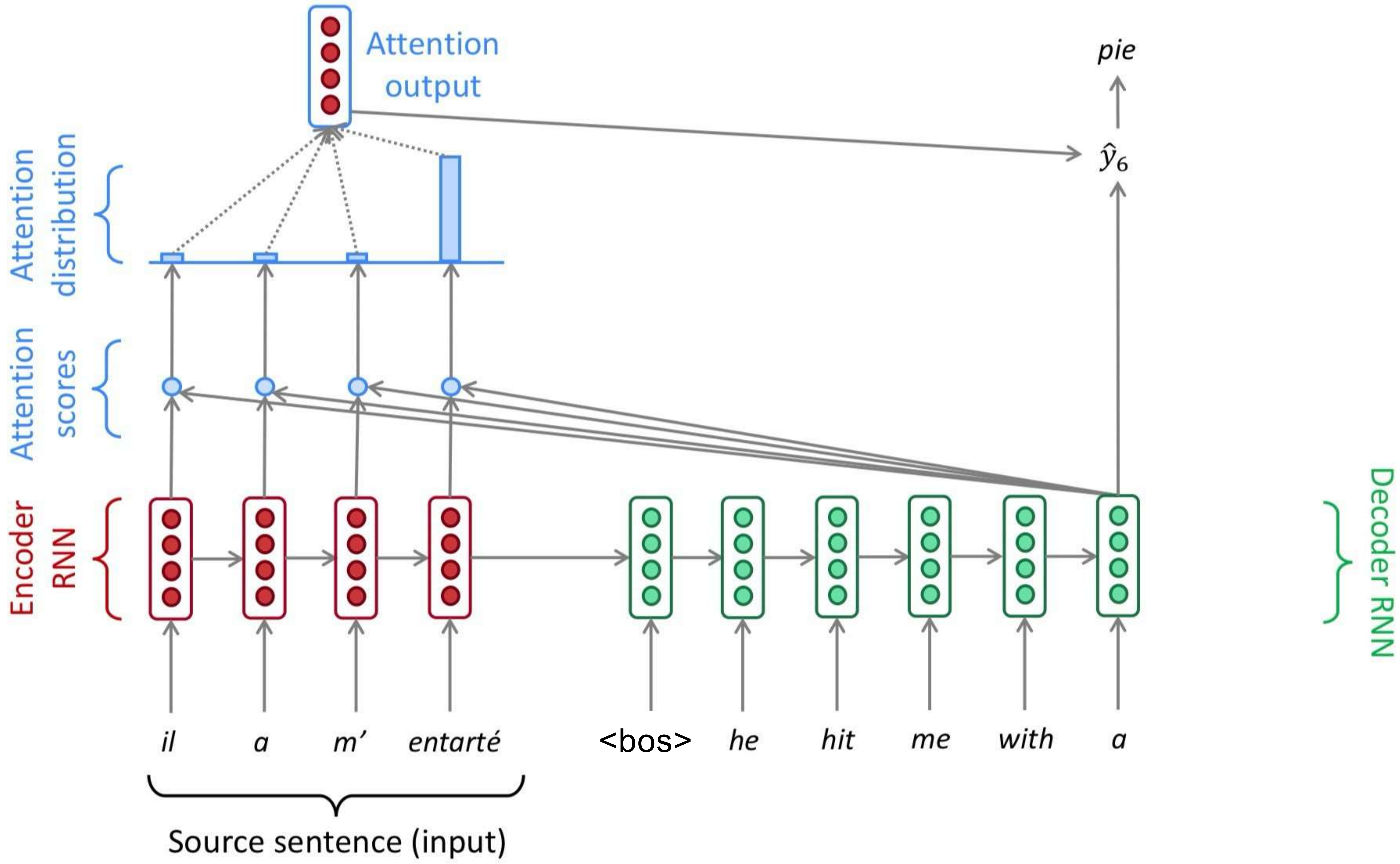
Seq2seq with attention



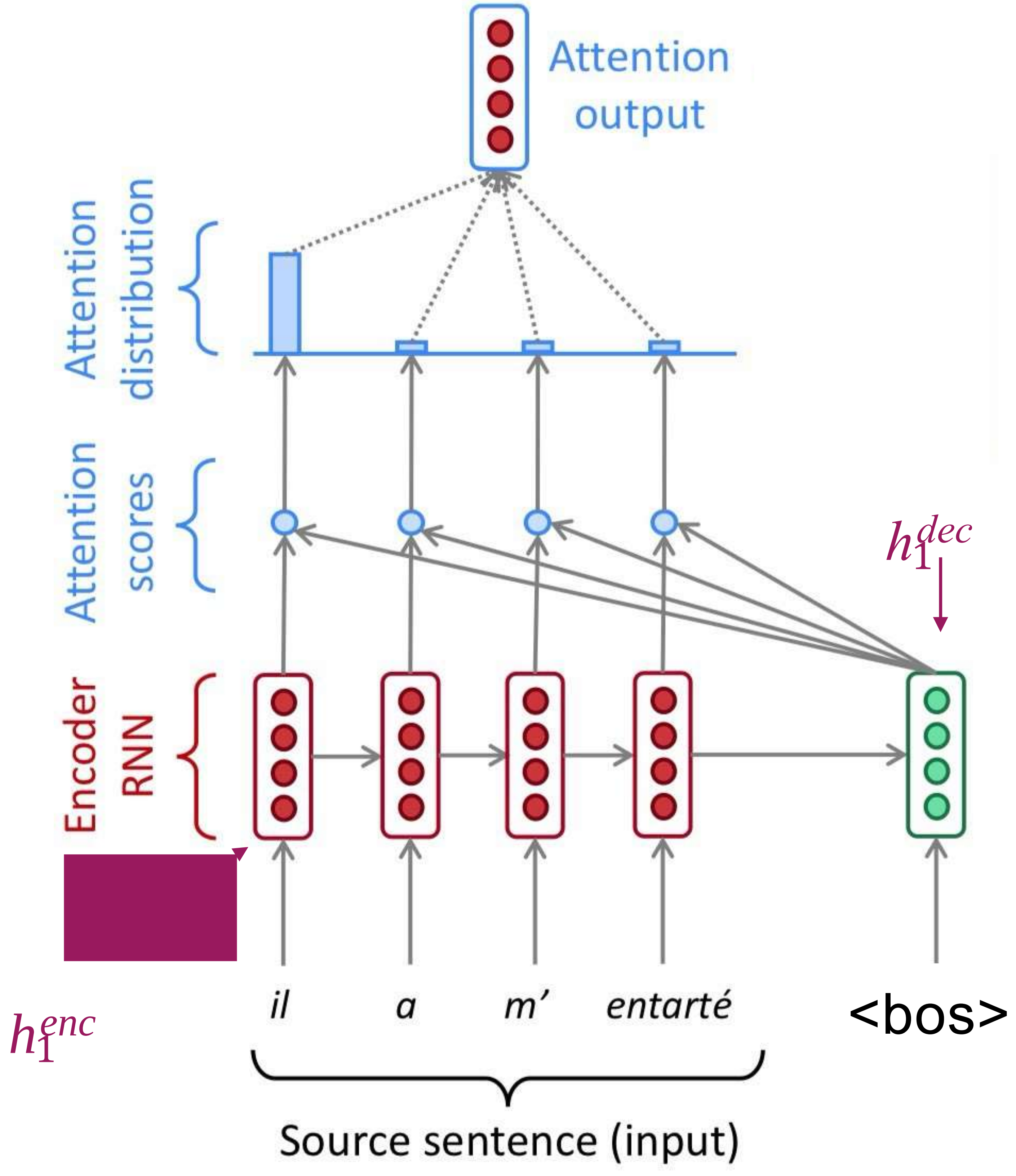

On this decoder timestep, we're mostly focusing on the first encoder hidden state (*"he"*)
Take softmax to turn the scores into a probability distribution
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<bos>
Source sentence (input)


Attention output
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 distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<bos>
Source sentence (input)


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 : 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

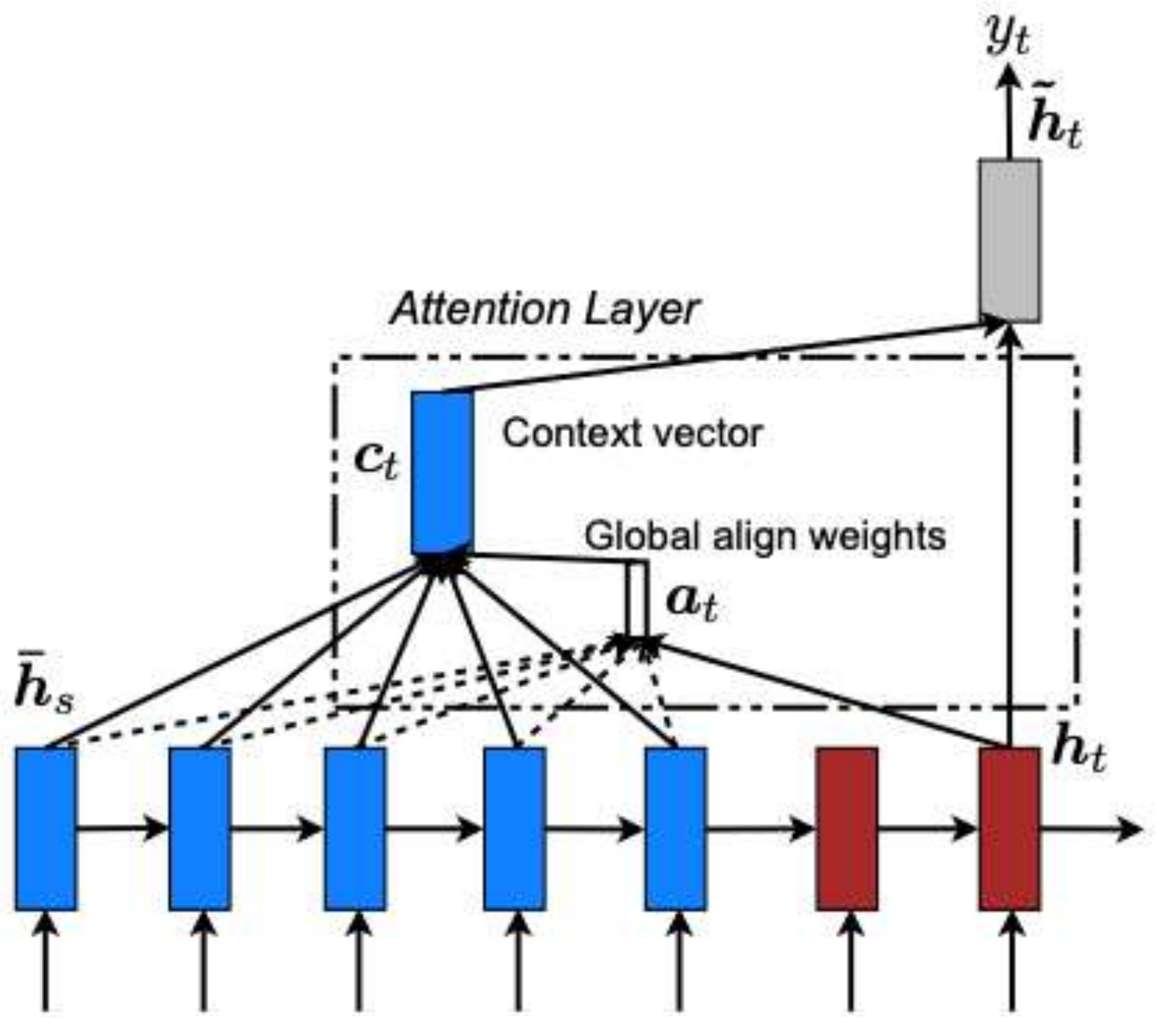
Neural Machine Translation by Jointly Learning to Align and Translate

Dzmitry Bahdanau
Jacobs University Bremen, Germany

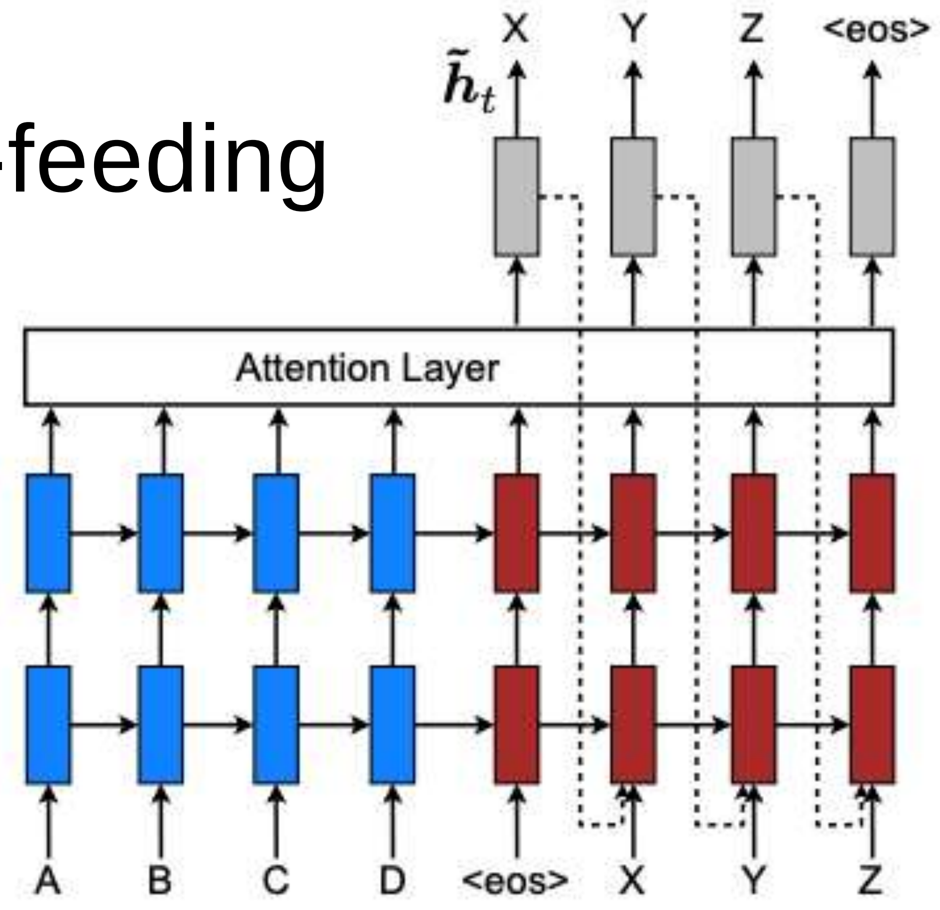
KyungHyun Cho **Yoshua Bengio***
Université de Montréal

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

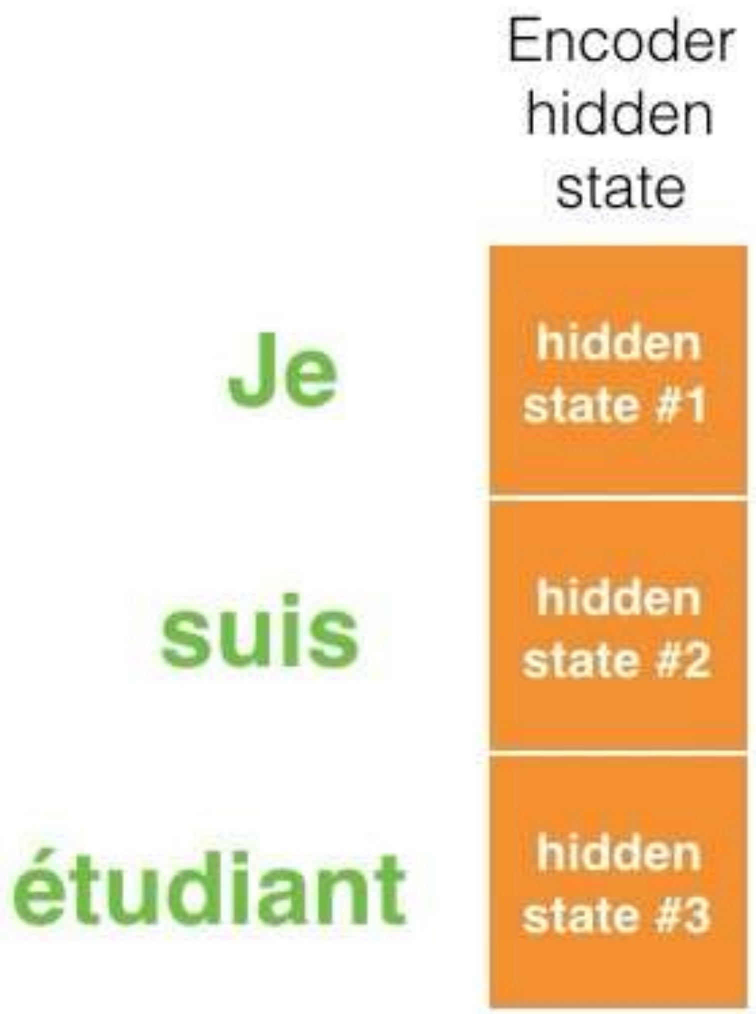


Computing attention

Attention at time step 4

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}):

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

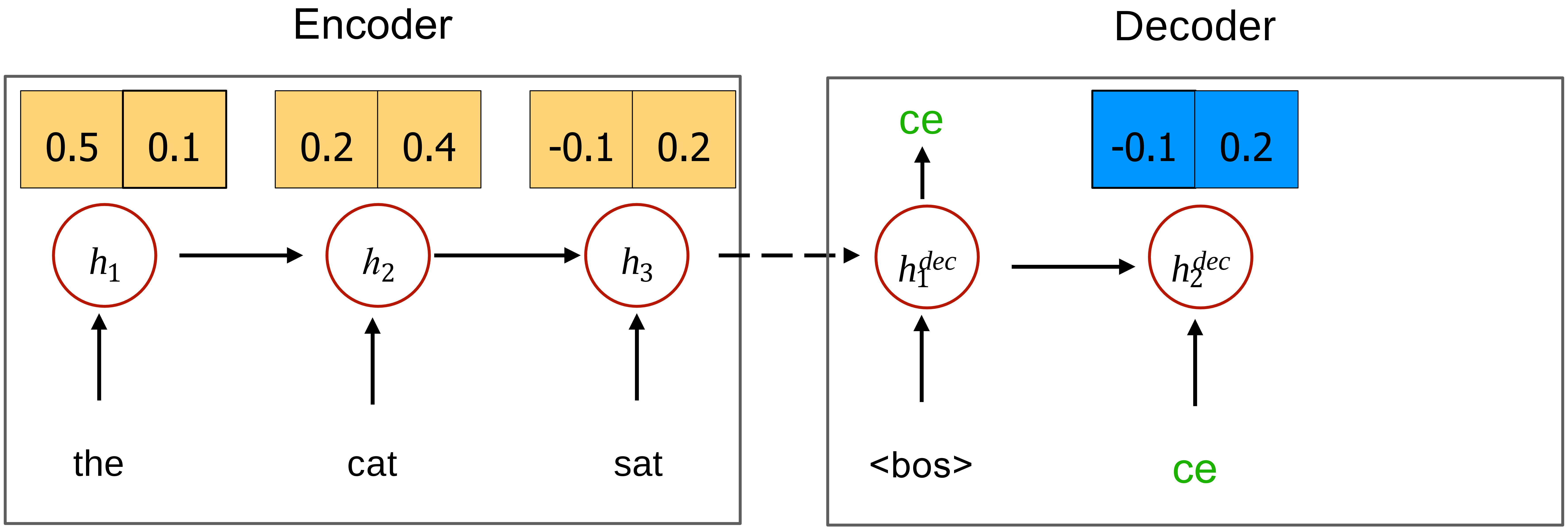
2. **Multiplicative attention:**

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



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

Dot-product attention:

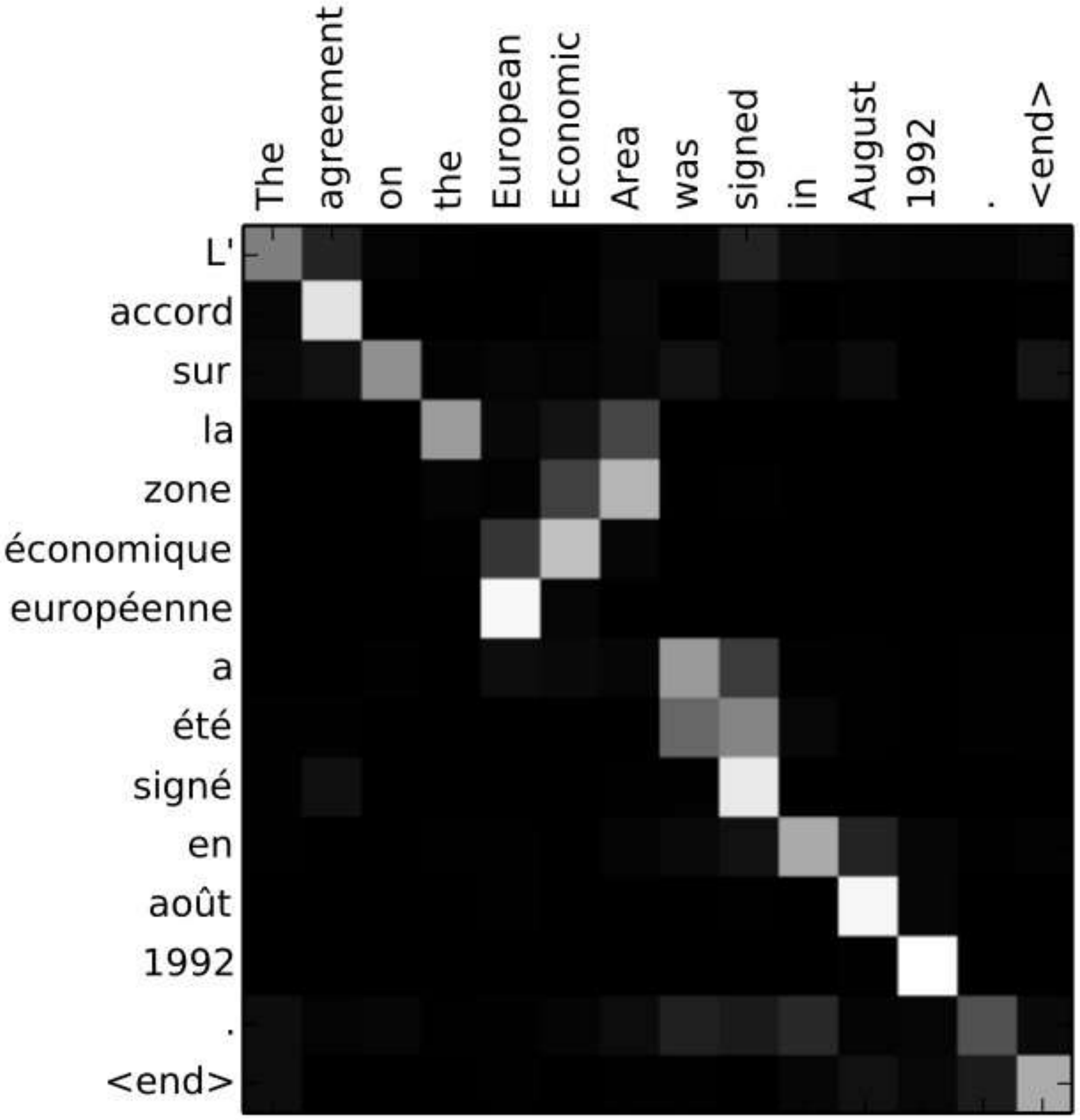
$$g(h_i^{enc}, h_t^{dec}) = h_t^{dec} \cdot h_i^{enc}$$

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)