Bài 10
Mô hình seq2seq và ứng dụng trong sinh văn bản
(seq2seq and application for text generation)

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Context

- Machine translation
- The seq2seq model
- Attention mechanism
- Machine translation with seq2seq
- Google’s Neural Machine Translation

Machine Translation

<u>**Machine Translation (MT)**</u> is the task of translating a sentence *x* from one language (the source language) to a sentence *y* in another language (the target language).

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

$\downarrow$

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

1990s-2010s: Statistical Machine Translation

- Core idea: Learn a probabilistic model from data
- Suppose we're translating French → English.
- We want to find best English sentence *y*, given French sentence *x*

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

- Use Bayes Rule to break this down into two components to be learned separately:

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

Translation Model

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

Language Model

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

1990s–2010s: Statistical Machine Translation

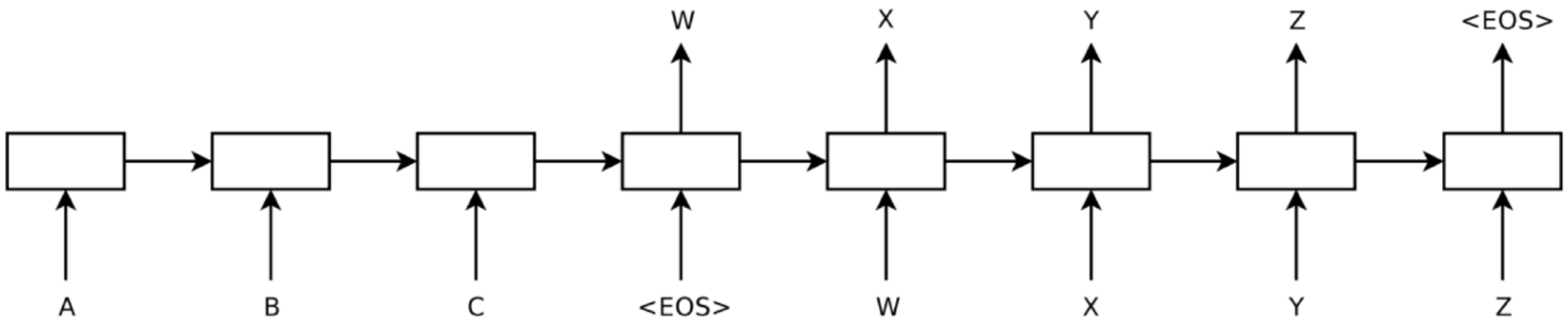
- SMT was a huge research field
- The best systems were extremely complex
  - Hundreds of important details
- Systems had many separately-designed subcomponents
  - Lots of feature engineering
    - Need to design features to capture particular language phenomena
  - Required compiling and maintaining extra resources
    - Like tables of equivalent phrases
  - Lots of human effort to maintain
    - Repeated effort for each language pair!

What is Neural Machine Translation?

- Neural Machine Translation (NMT) is a way to do Machine Translation with a *single neural network*

- The neural network architecture is called sequence-to-sequence (aka seq2seq) and it involves *two* RNNs.

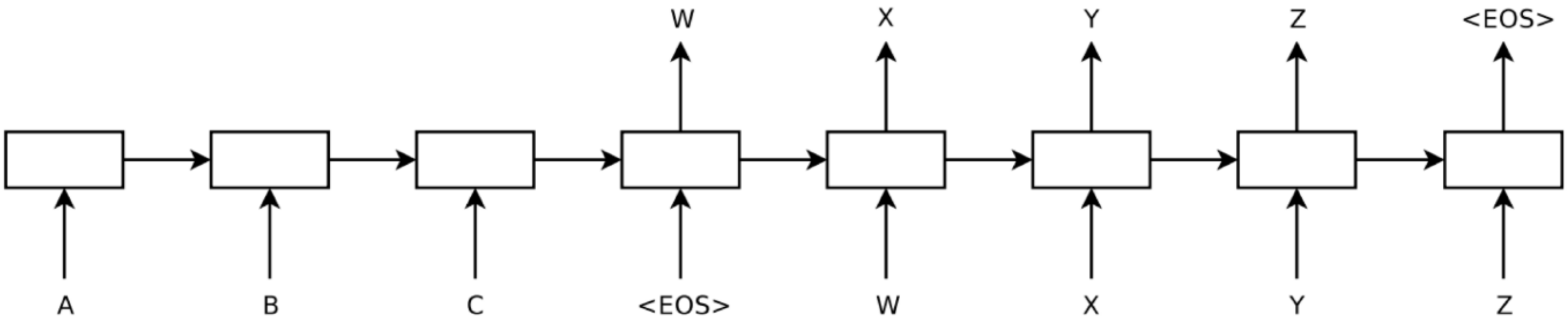
Encoder-decoder Framework



“Sequence to Sequence Learning with Neural Networks”, 2014

Encoder-decoder Framework

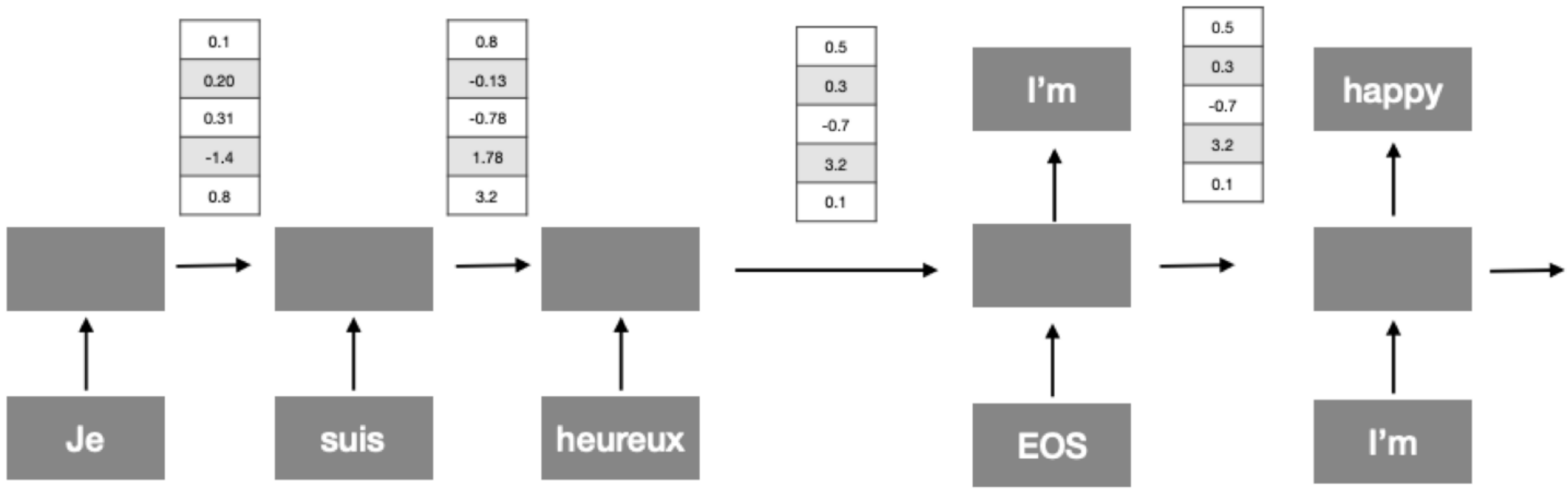
Vectơ K chiều của ngữ cảnh



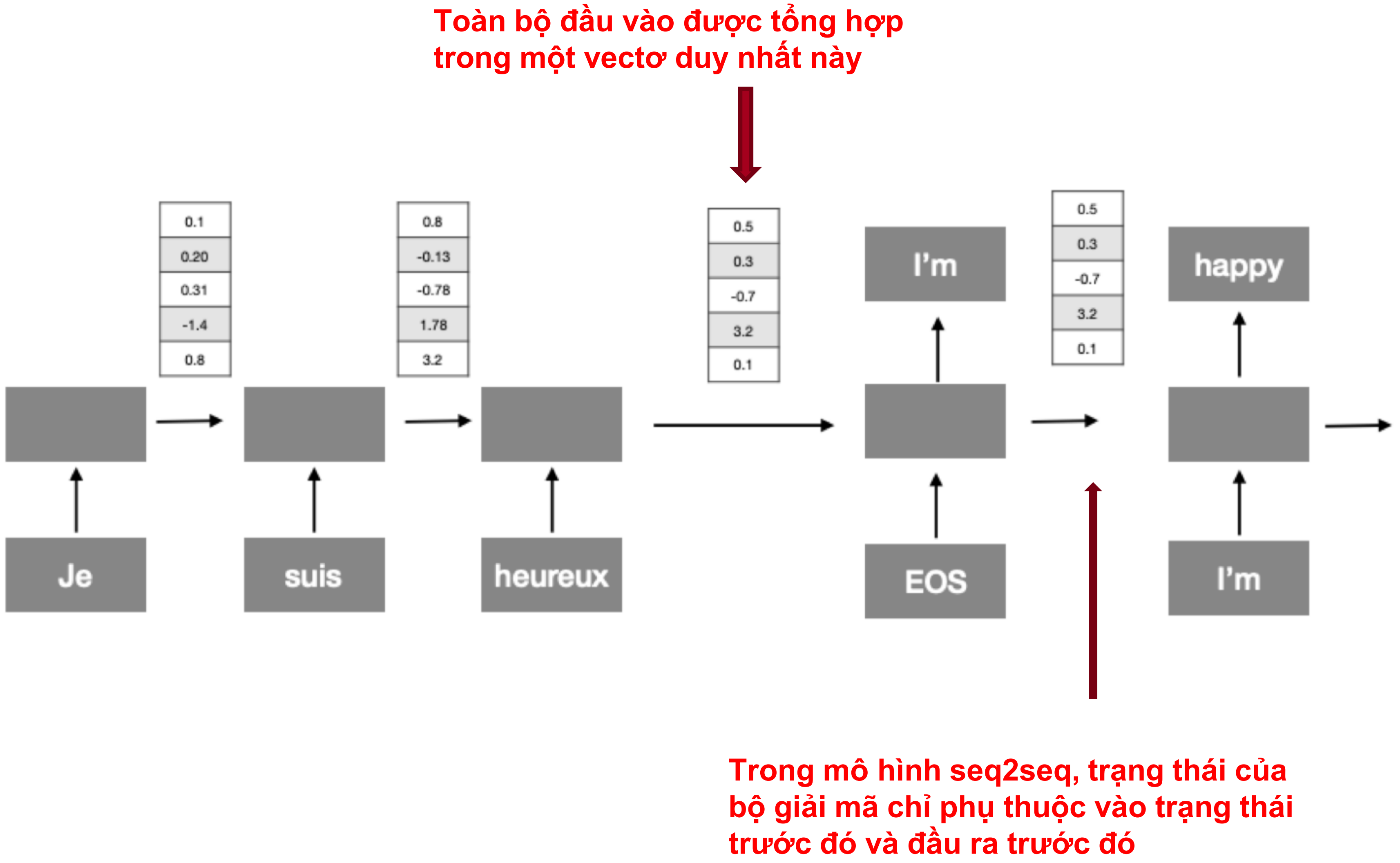
Điều kiện của từ được sinh ra trong bản dịch

"Sequence to Sequence Learning with Neural Networks", 2014

Encoder-decoder Framework

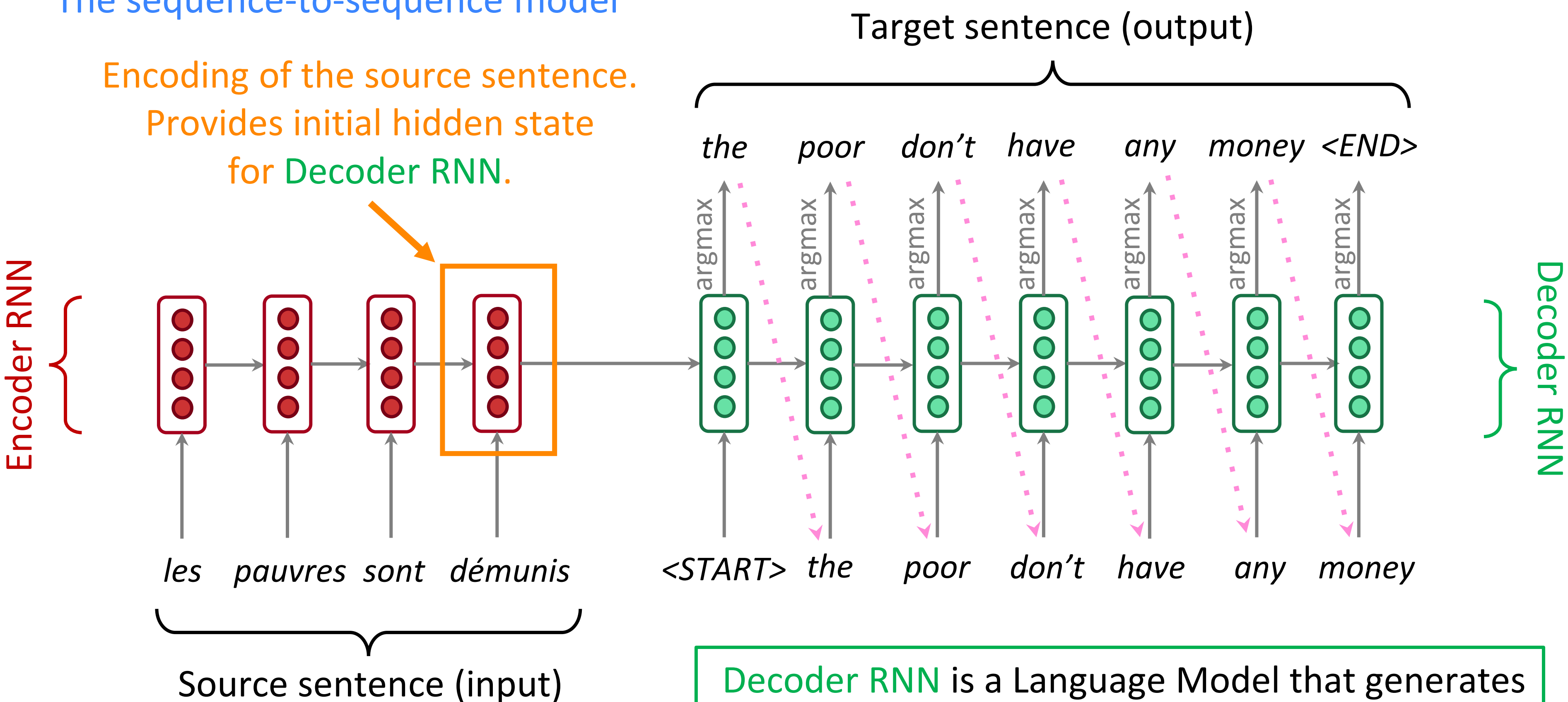


Encoder-decoder Framework



Neural Machine Translation (NMT)

The sequence-to-sequence model



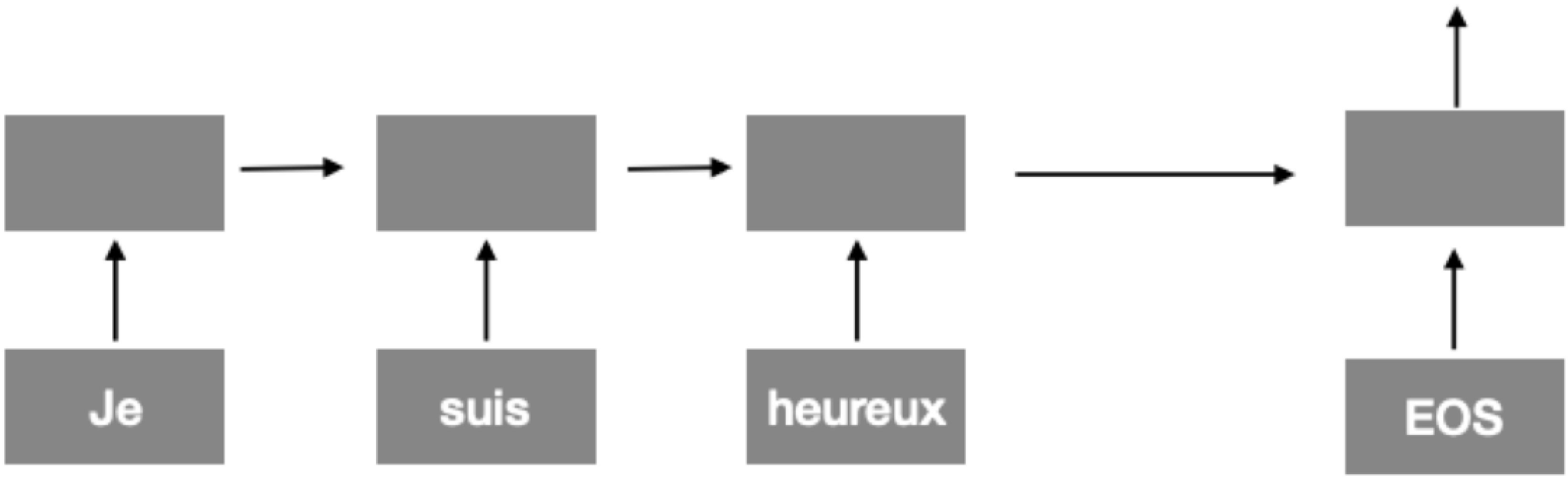
Decoder RNN is a Language Model that generates target sentence conditioned on encoding.

Encoder RNN produces an encoding of the source sentence.

Note: This diagram shows **test time** behavior: decoder output is fed in ····➔ as next step's input

Training

- Như trong mô hình RNN khác, chúng ta có thể huấn luyện bằng cách minimizing hàm loss giữa những gì chúng ta dự đoán ở mỗi bước và giá trị đúng của nó.



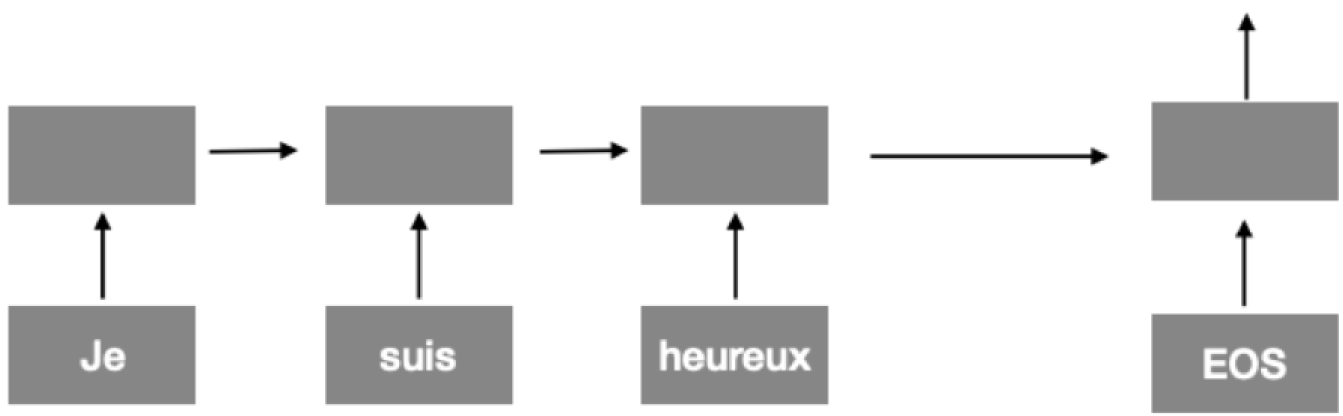
Training

Truth

I'm	you	are	the	…
1	0	0	0	0

Predicted

I'm	you	are	the	…
0.03	0.05	0.02	0.01	0.009

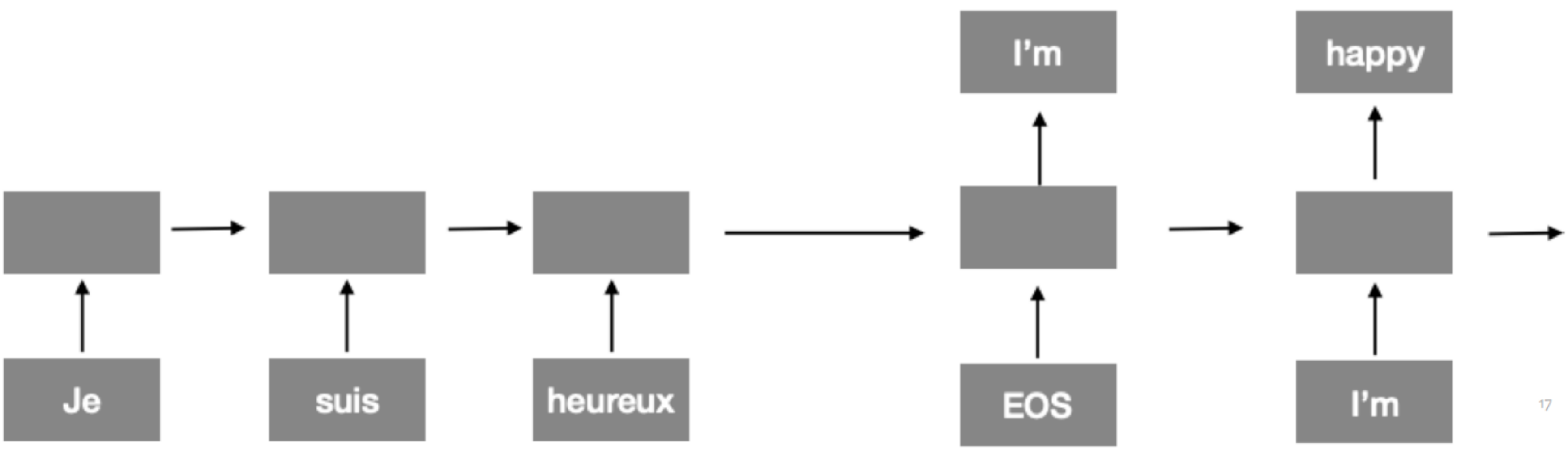


Truth

happy	great	bad	ok	...
1	0	0	0	0

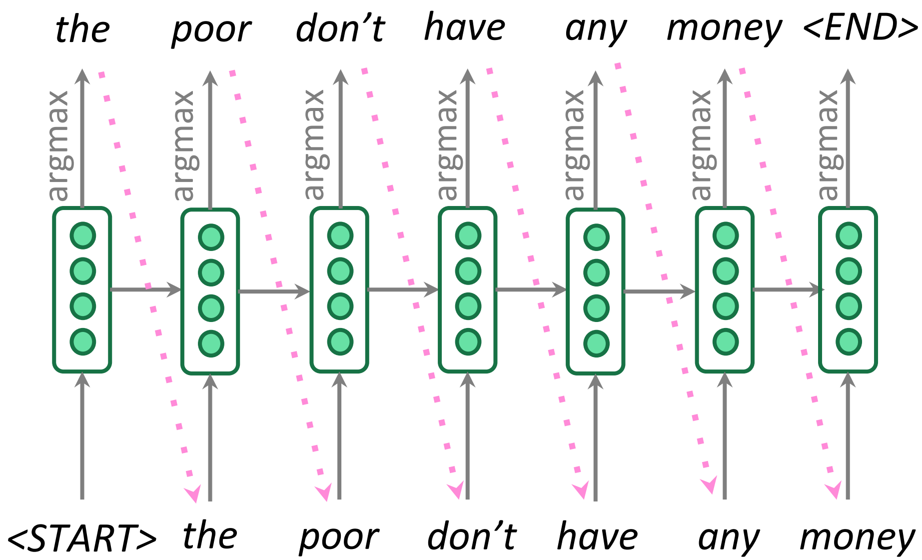
Predicted

happy	great	bad	ok	...
0.13	0.08	0.01	0.03	0.009



Better-than-greedy decoding?

- We showed how to generate (or "decode") the target sentence by taking argmax on each step of the decoder



- This is greedy decoding (take most probable word on each step)
- **Problems?**

Better-than-greedy decoding?

- Greedy decoding has no way to undo decisions!
  - *les pauvres sont démunis (the poor don't have any money)*
  - → *the* ____
  - → *the poor* ____
  - → *the poor are* ____
- Better option: use beam search (a search algorithm) to explore *several* hypotheses and select the best one

Giải mã dựa vào Beam search

- Ideally we want to find *y* that maximizes

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

- We could try enumerating all *y* → too expensive!
  - Complexity $O(V^T)$ where *V* is vocab size and *T* is target sequence length

- Beam search: On each step of decoder, keep track of the *k* most probable partial translations
  - *k* is the beam size (in practice around 5 to 10)
  - Not guaranteed to find optimal solution
  - But much more efficient!

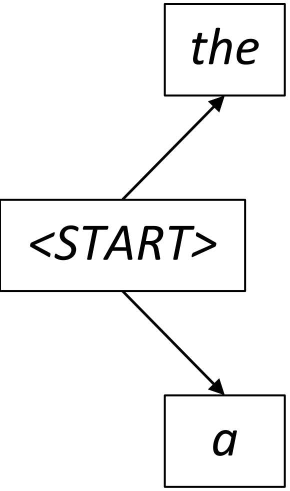
Giải mã dựa vào Beam search: ví dụ

Beam size = 2

<START>

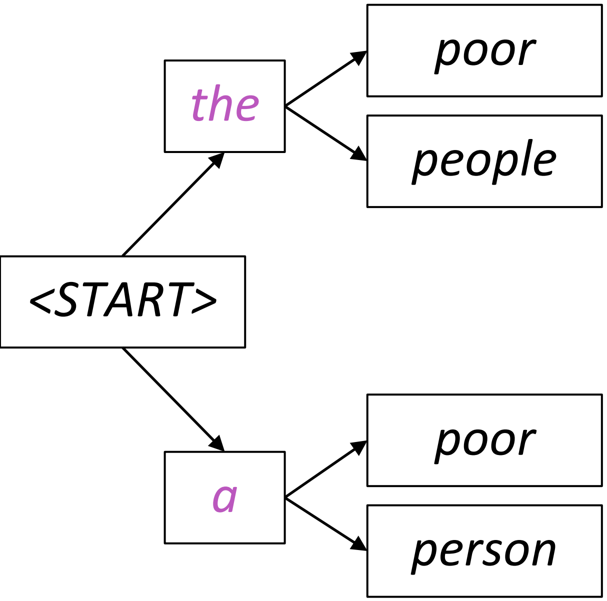
Giải mã dựa vào Beam search: ví dụ

Beam size = 2



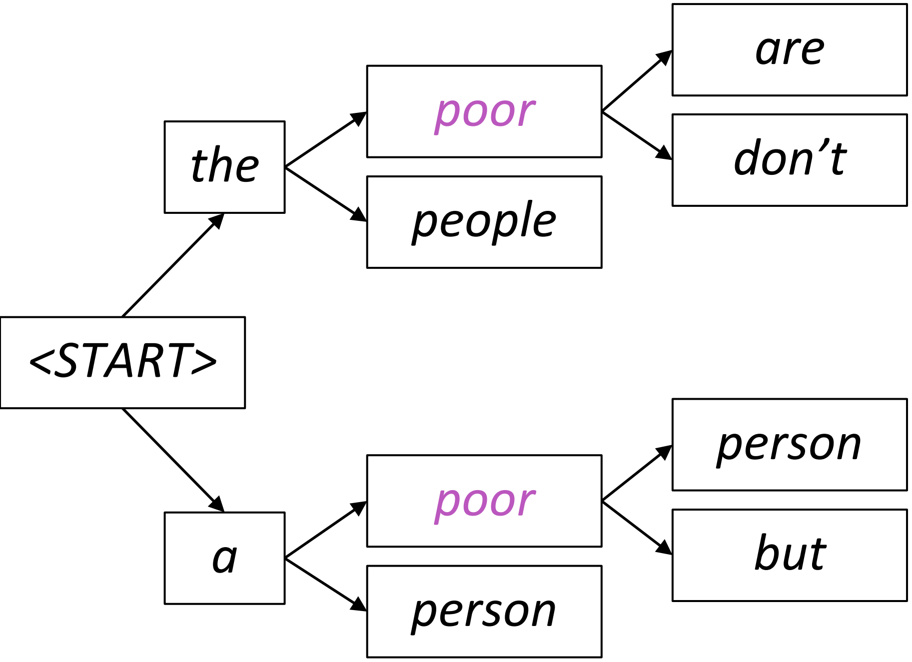
Giải mã dựa vào Beam search: ví dụ

Beam size = 2



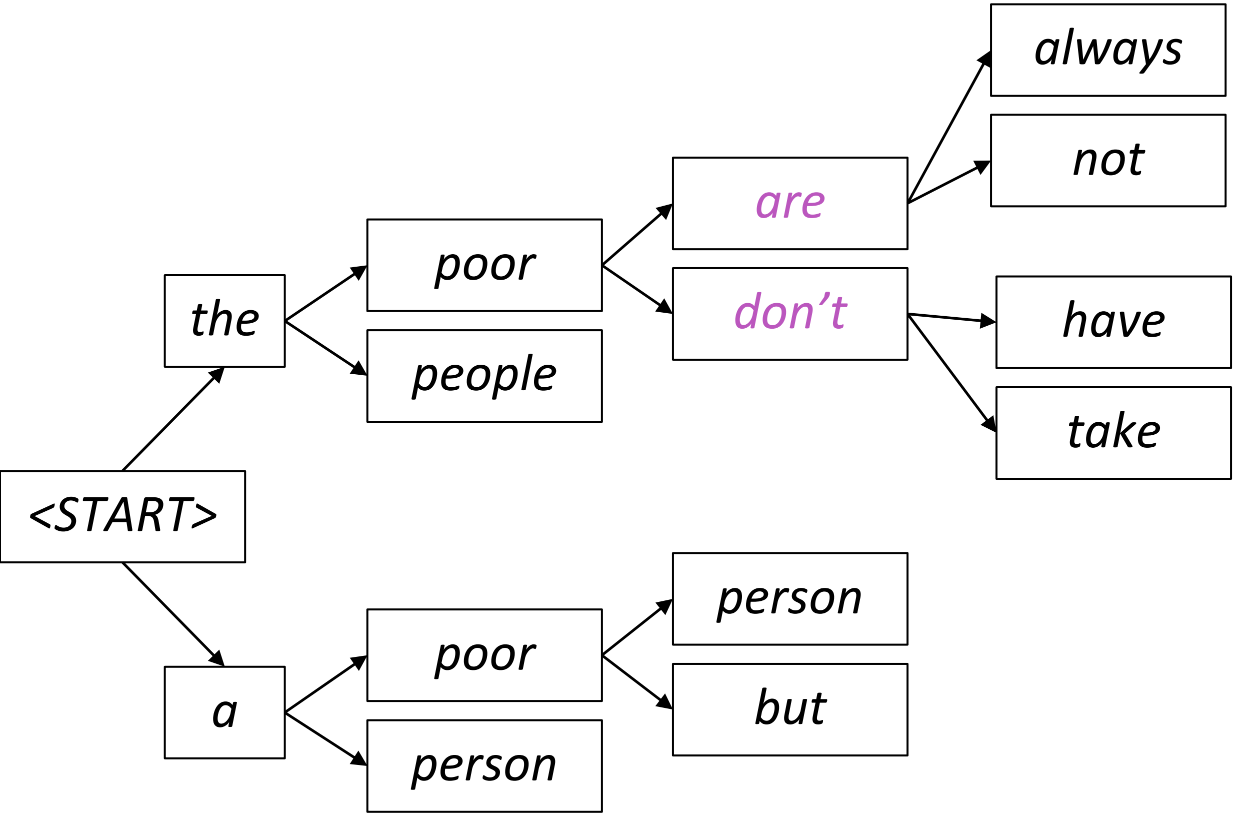
Giải mã dựa vào Beam search: ví dụ

Beam size = 2



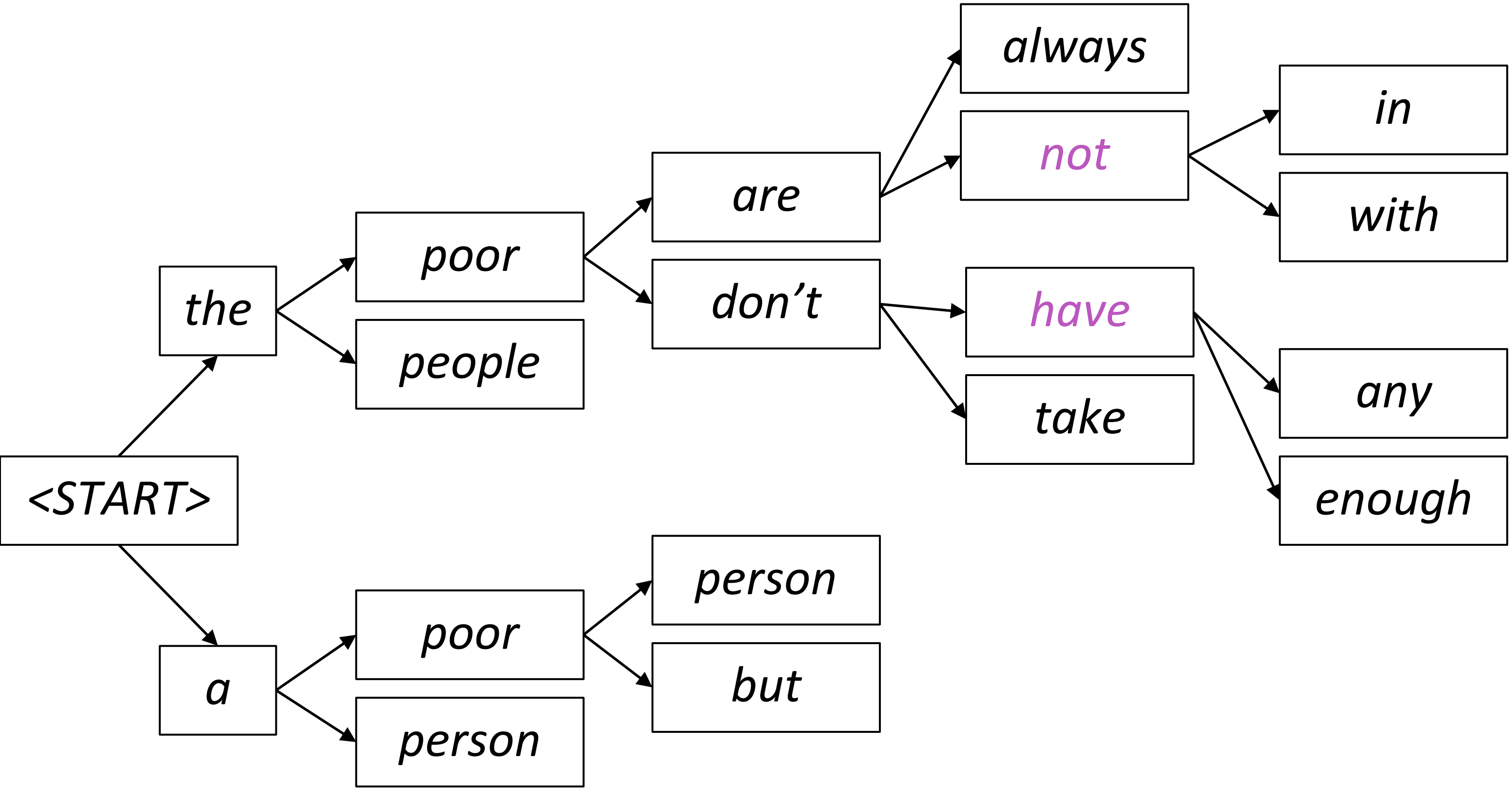
Giải mã dựa vào Beam search: ví dụ

Beam size = 2



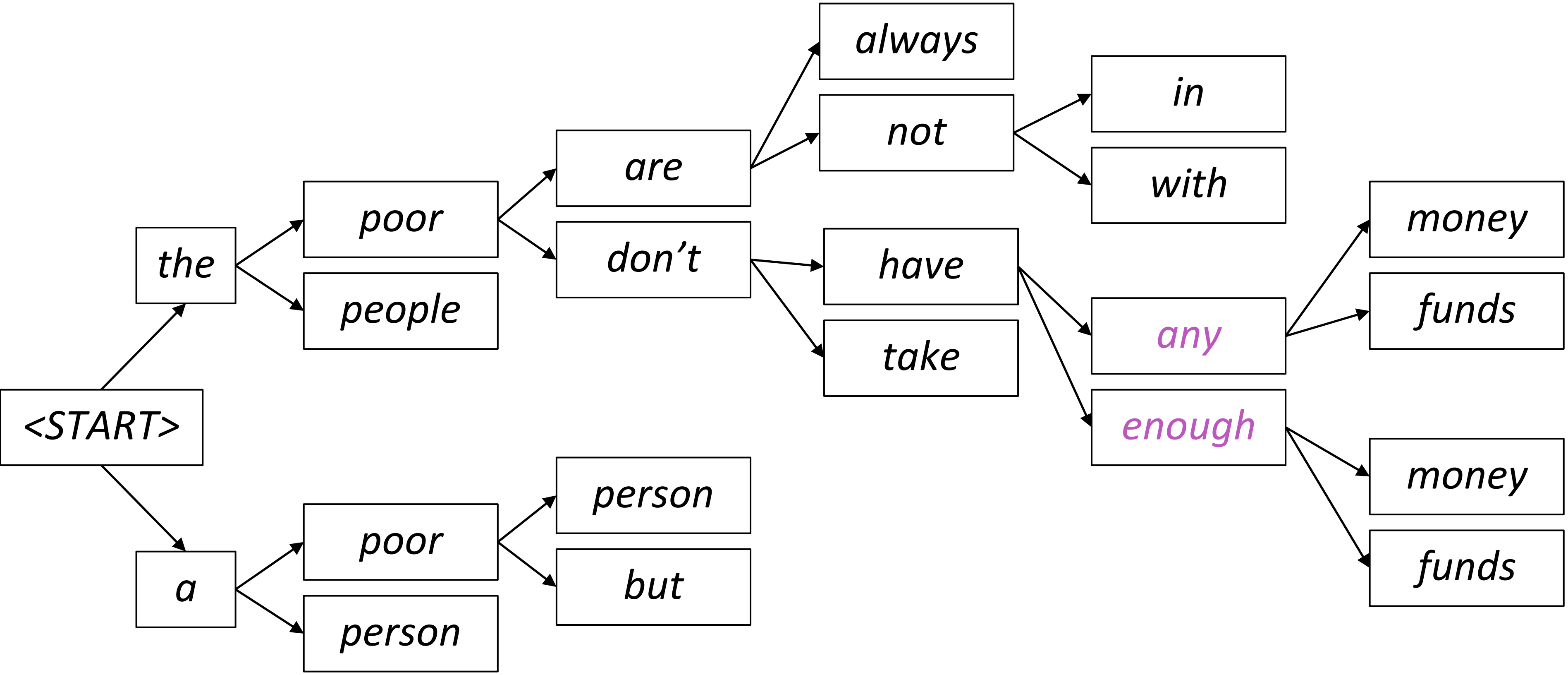
Giải mã dựa vào Beam search: ví dụ

Beam size = 2



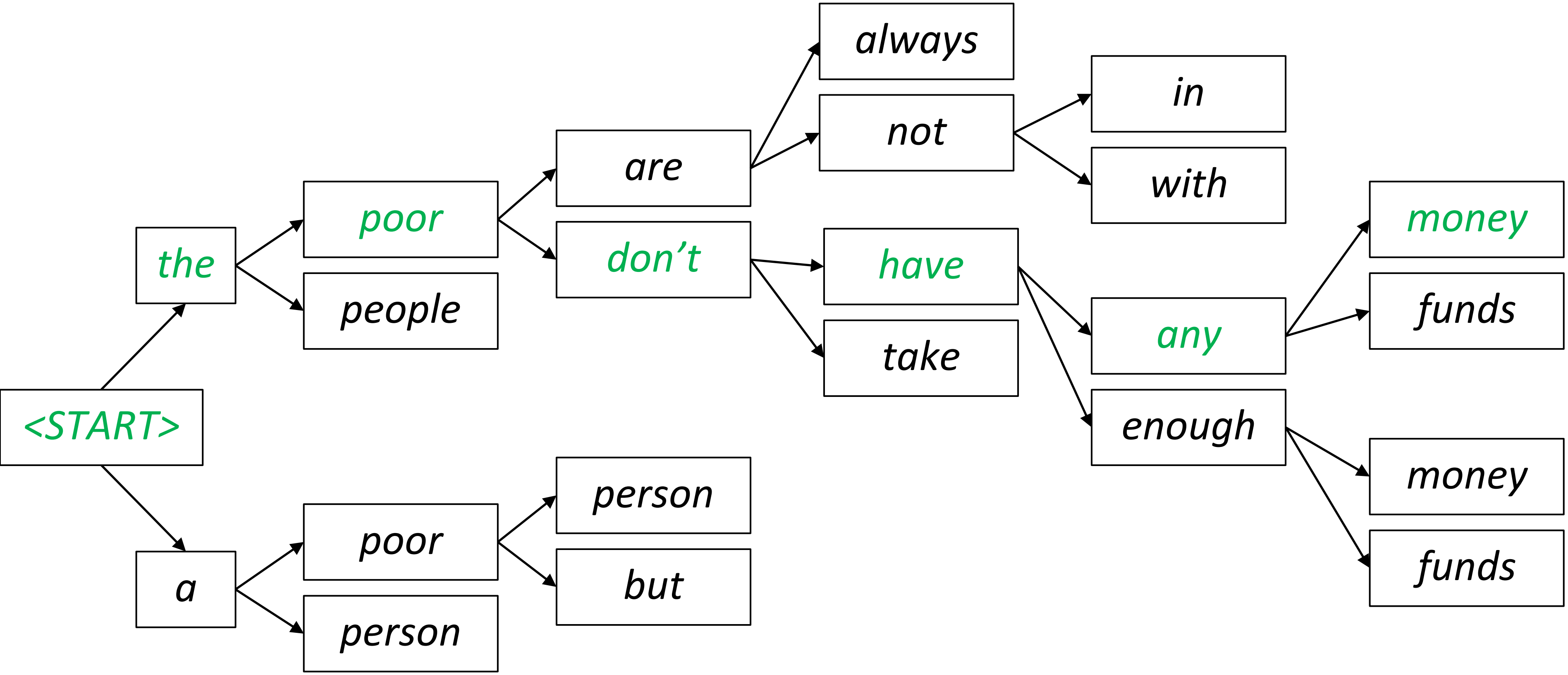
Giải mã dựa vào Beam search: ví dụ

Beam size = 2



Giải mã dựa vào Beam search: ví dụ

Beam size = 2



Beam search: Tiêu chí stopping

- Trong giải mã tham lam, chúng ta thường giải mã cho đến khi mô hình sinh ra token <END>

Ví dụ : *<START> he hit me with a pie <END>*

- Trong giải mã beam search, các giả thuyết khác nhau có thể tạo ra token <END> ở các bước thời gian khác nhau.
  - Khi một giả thuyết sinh ra <END>, thì giả thuyết đó đã hoàn thành.
  - Đặt nó sang một bên và tiếp tục khám phá các giả thuyết khác thông qua beam Search.
- Thông thường, chúng tôi tiếp tục beam search cho đến khi:
  - Chúng ta đạt đến bước thời gian T (T là một số ngưỡng đã được xác định trước) hoặc
  - Chúng ta có ít nhất n giả thuyết đã hoàn thành (trong đó n là ngưỡng được xác định trước)

Beam search: Kết thúc

- We have our list of completed hypotheses.
- How to select top one with highest score?

- Each hypothesis $y_1, \ldots, y_t$ on our list has a score

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

- <u>Problem with this:</u> longer hypotheses have lower scores

- <u>Fix:</u> Normalize by length. Use this to select top one instead:

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

Advantages of NMT

Compared to SMT, NMT has many advantages:

- Better performance
  - More fluent
  - Better use of context
  - Better use of phrase similarities

- A single neural network to be optimized end-to-end
  - No subcomponents to be individually optimized

- Requires much less human engineering effort
  - No feature engineering
  - Same method for all language pairs

Disadvantages of NMT

Compared to SMT:

- NMT is less interpretable
  - Hard to debug

- NMT is difficult to control
  - For example, can’t easily specify rules or guidelines for translation
  - Safety concerns!

How do we evaluate Machine Translation?

BLEU (**Bil**ingual **E**valuation **U**nderstudy)

- BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:
  - *n*-gram precision (usually up to 3 or 4-grams)
  - Penalty for too-short system translations

- BLEU is useful but imperfect
  - There are many valid ways to translate a sentence
  - So a good translation can get a poor BLEU score because it has low *n*-gram overlap with the human translation ☹

How do we evaluate Machine Translation?

- Precision n-gram = Number of correct predicted n-grams /
  Number of total predicted n-grams

- **Correct sentence:** *The guard arrived late because it was raining*
- **Predicted sentence:** *The guard arrived late because of the rain*

Precision 1-gram ($p1$) = 5 / 8

Precision 2-gram ($p2$)= 4 / 7

recision 3-gram ($p3$) = 3 / 6

Precision 4-gram ($p4$) = 2 / 5

How do we evaluate Machine Translation?

- **Geometric Average Precision Scores**

$$
\begin{aligned}
Geometric\ Average\ Precision\ (N) &= exp(\sum_{n=1}^{N} w_n \ log \ p_n) \\
&= \prod_{n=1}^{N} {p_n}^{w_n} \\
&= (p_1)^{\frac{1}{4}} \cdot (p_2)^{\frac{1}{4}} \cdot (p_3)^{\frac{1}{4}} \cdot (p_4)^{\frac{1}{4}}
\end{aligned}
$$

How do we evaluate Machine Translation?

- **Correct sentence:** *The guard arrived late because it was raining*
- **Predicted sentence:** *The late*

  Precision 1-gram (*p*1) = 2 / 2

  Precision 2-gram (*p*2)= 1 / 1

  ➢ khuyến khích model sinh đầu ra ngắn hơn và điểm cao hơn.

- **Brevity Penalty:** phạt những câu quá ngắn

$$Brevity\ Penalty = \begin{cases} 1, & \text{if } c > r \\ e^{(1-r/c)}, & \text{if } c <= r \end{cases}$$

- c là *predicted length* = số lượng từ có trong predicted sentence
- r là *target length* = số lượng từ có trong target sentence

How do we evaluate Machine Translation?

- **BLEU score**

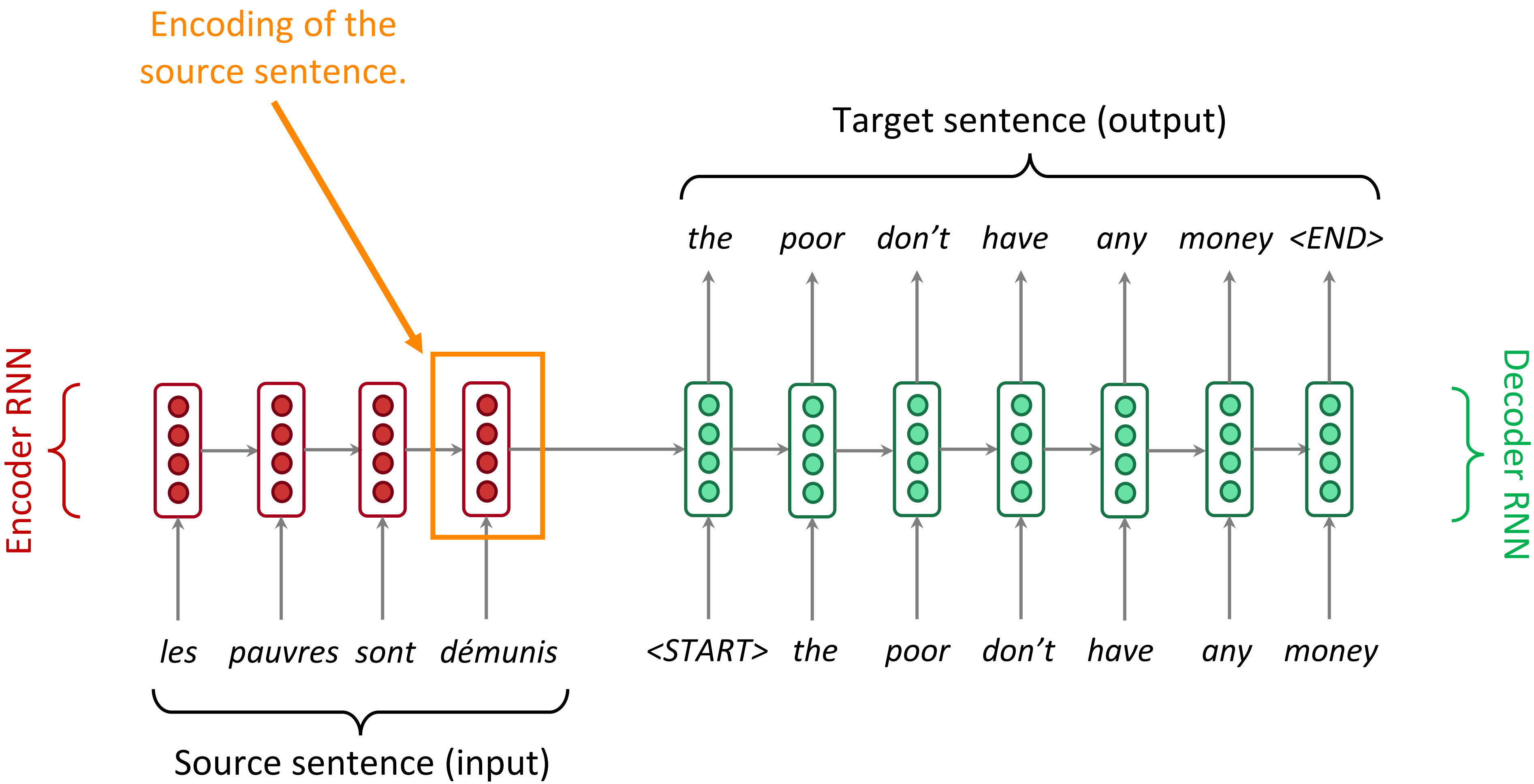
$$Bleu\ (N) = Brevity\ Penalty \cdot Geometric\ Average\ Precision\ Scores\ (N)$$

với N = số gram

- **Công thức BLEU khác**

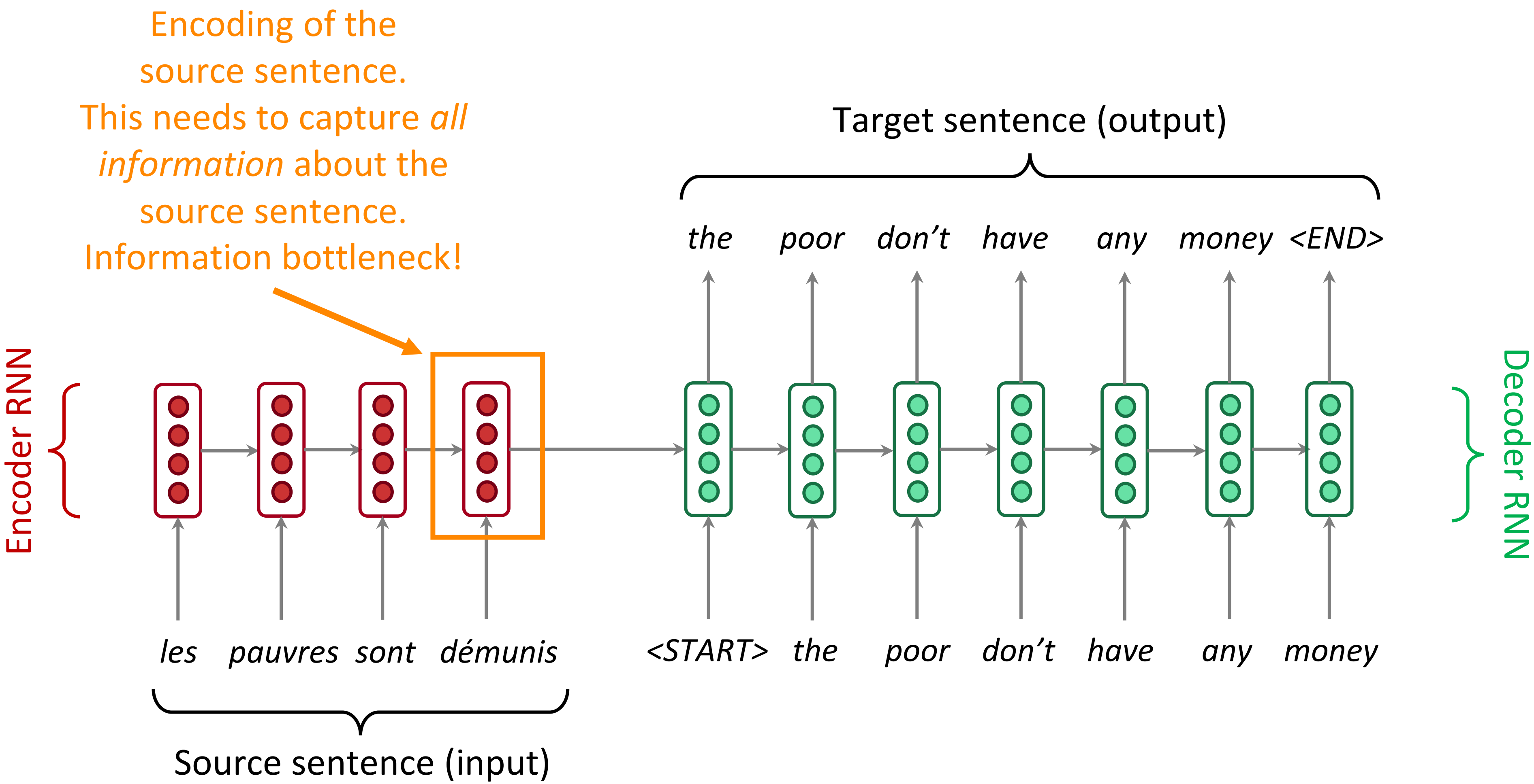
$$\begin{aligned} log\ Bleu &= min(1 - \frac{r}{c}, 0) + \sum_{n=1}^{4} \frac{log\ p_n}{4} \\ &= min(1 - \frac{r}{c}, 0) + \frac{log\ p_1 + log\ p_2 + log\ p_3 + log\ p_4}{4} \end{aligned}$$

Sequence-to-sequence: Vấn đế nút cổ chai



Problems with this architecture?

Sequence-to-sequence: the bottleneck problem

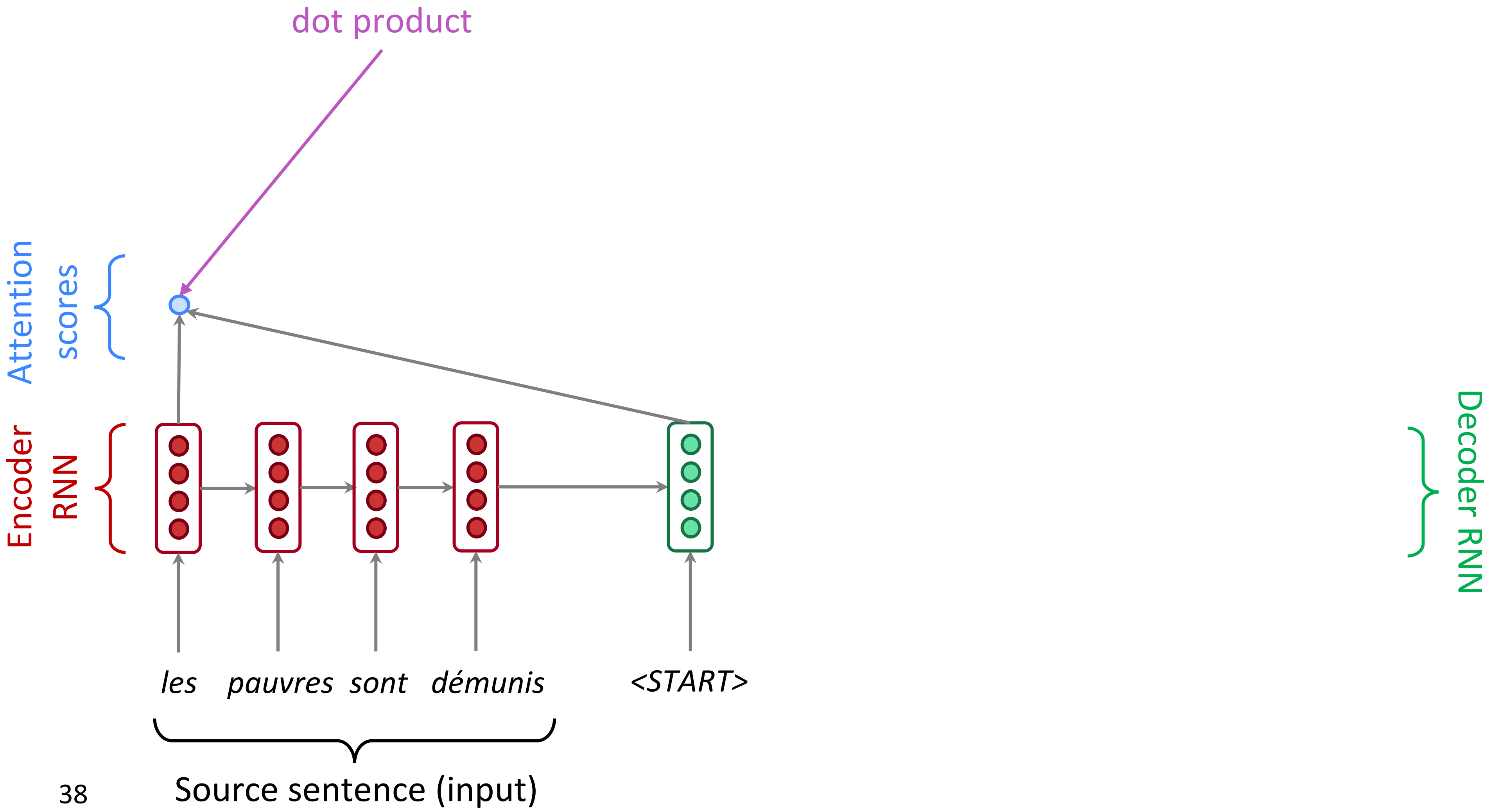


Attention

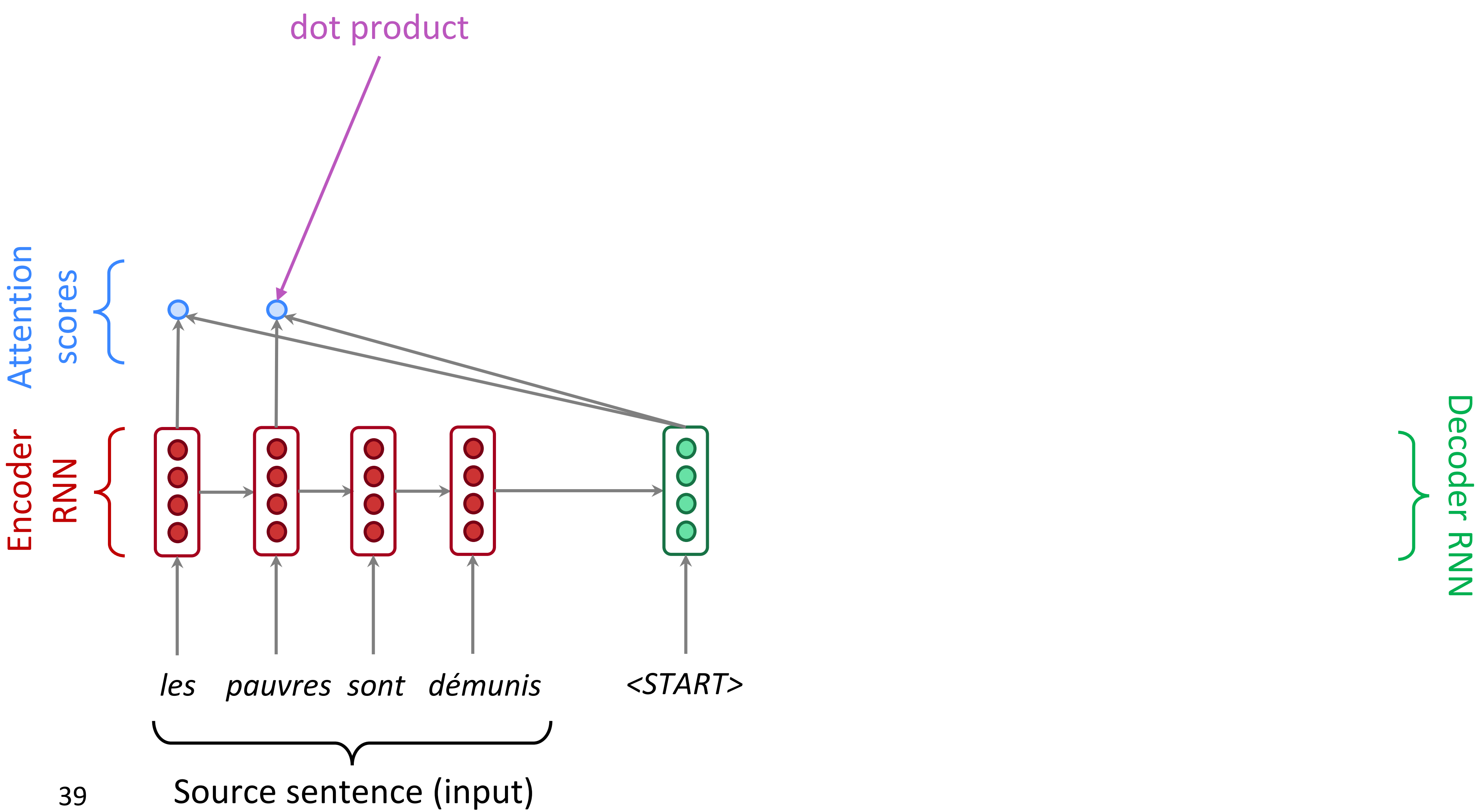
- **Attention** provides a solution to the bottleneck problem.

- Core idea: on each step of the decoder, *focus on a particular part* of the source sequence

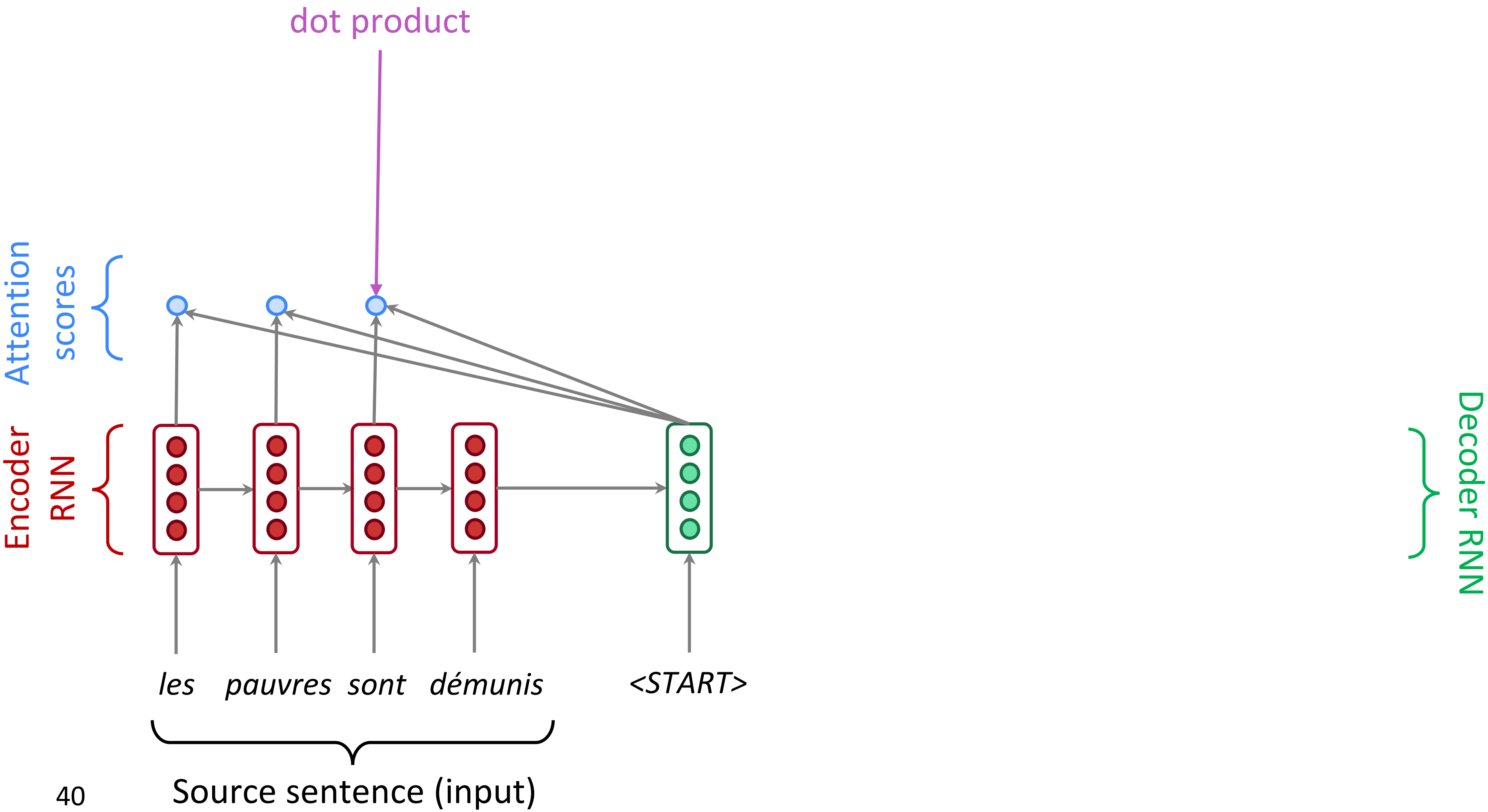
Encoder-Decoder với Attention



Seq2Seq với attention



Sequence-to-sequence with attention



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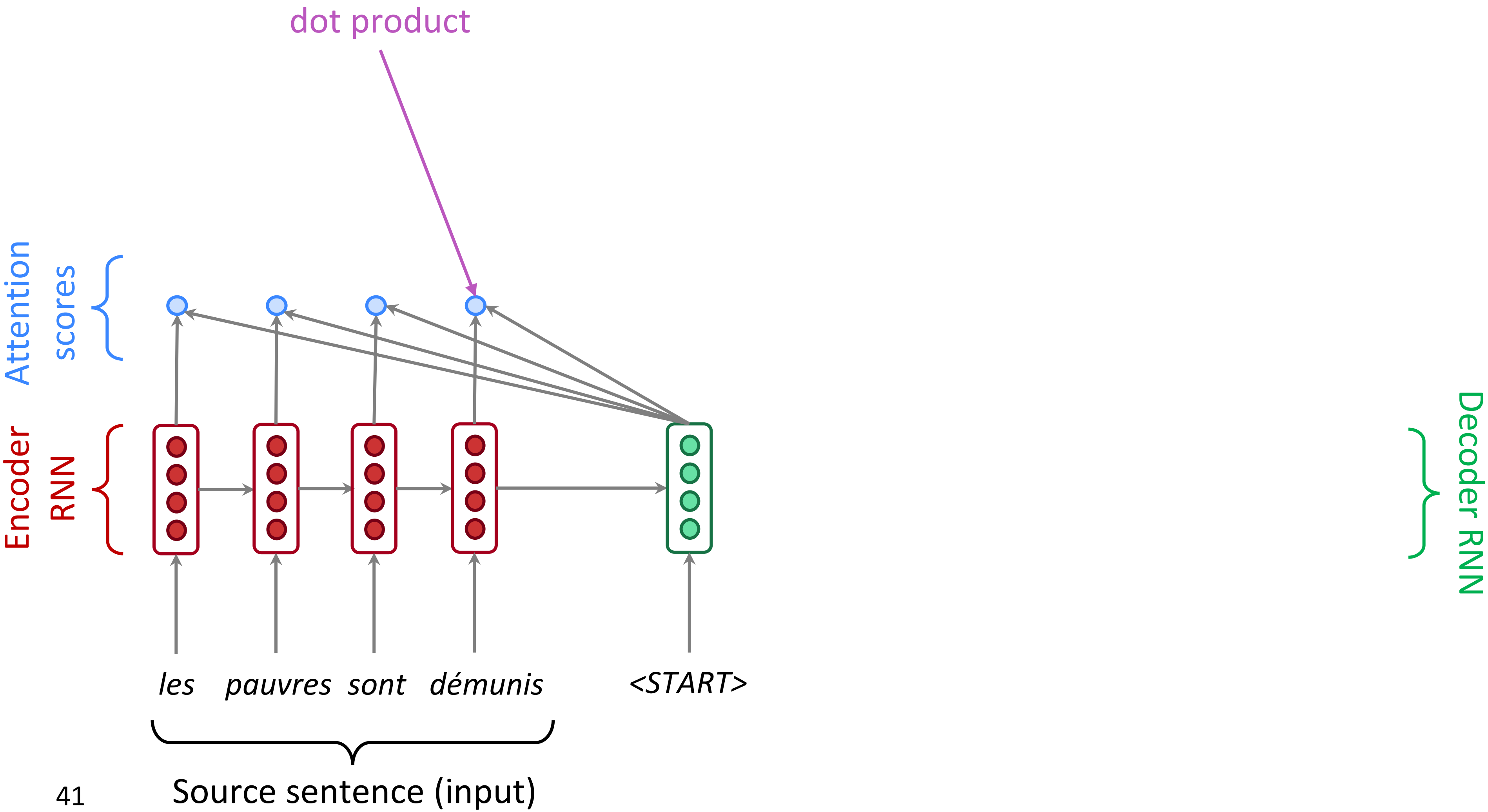

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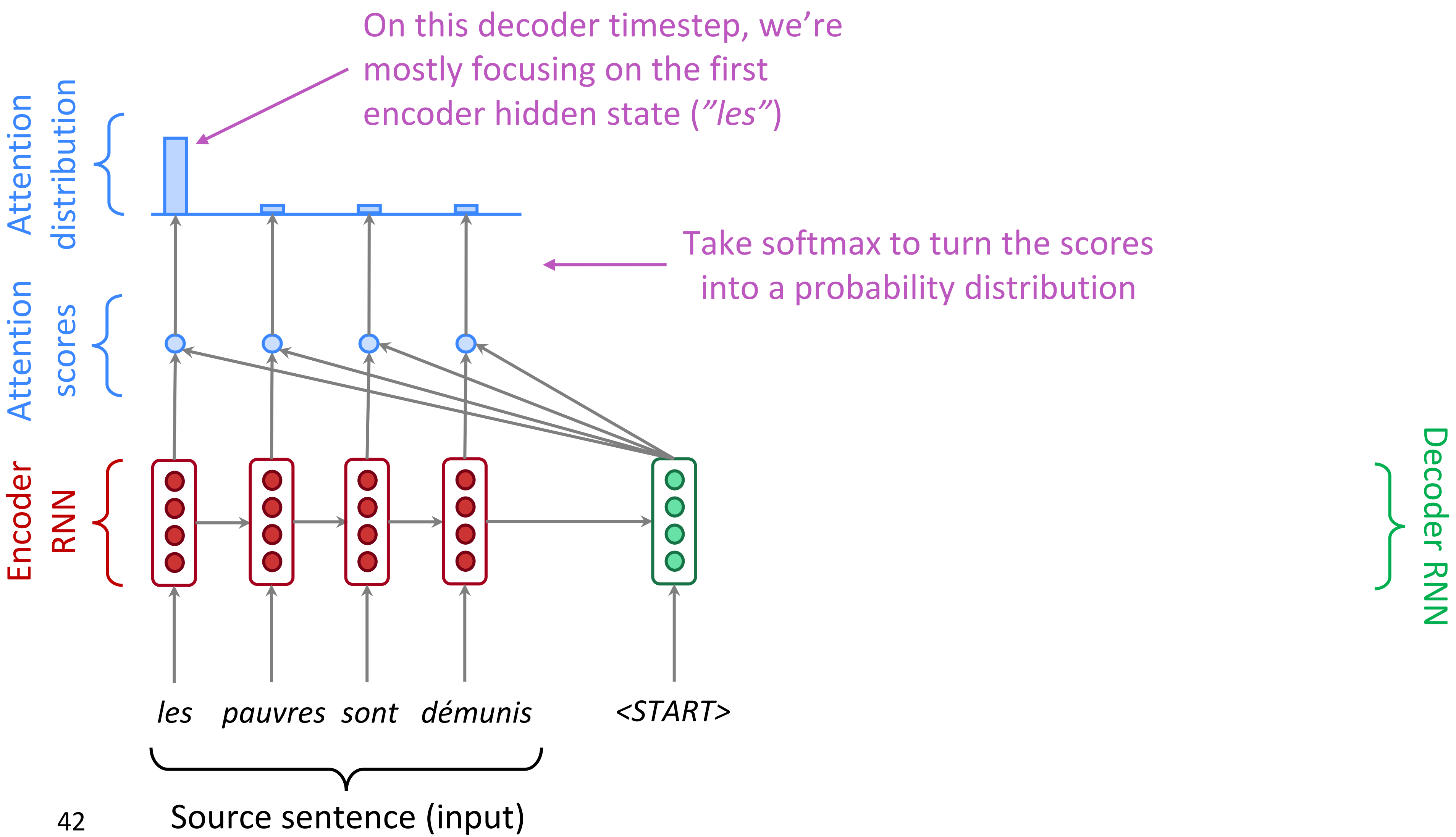
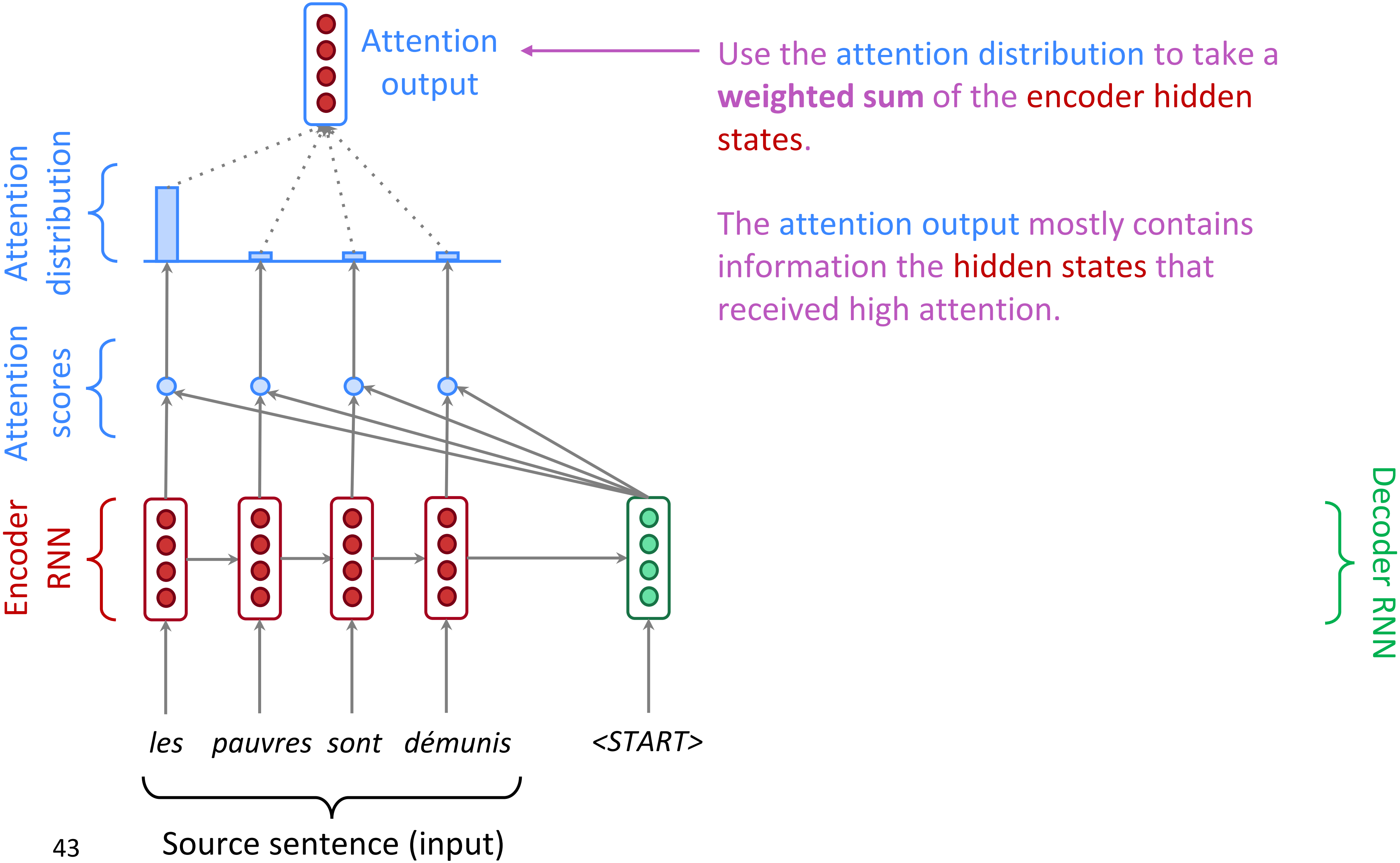


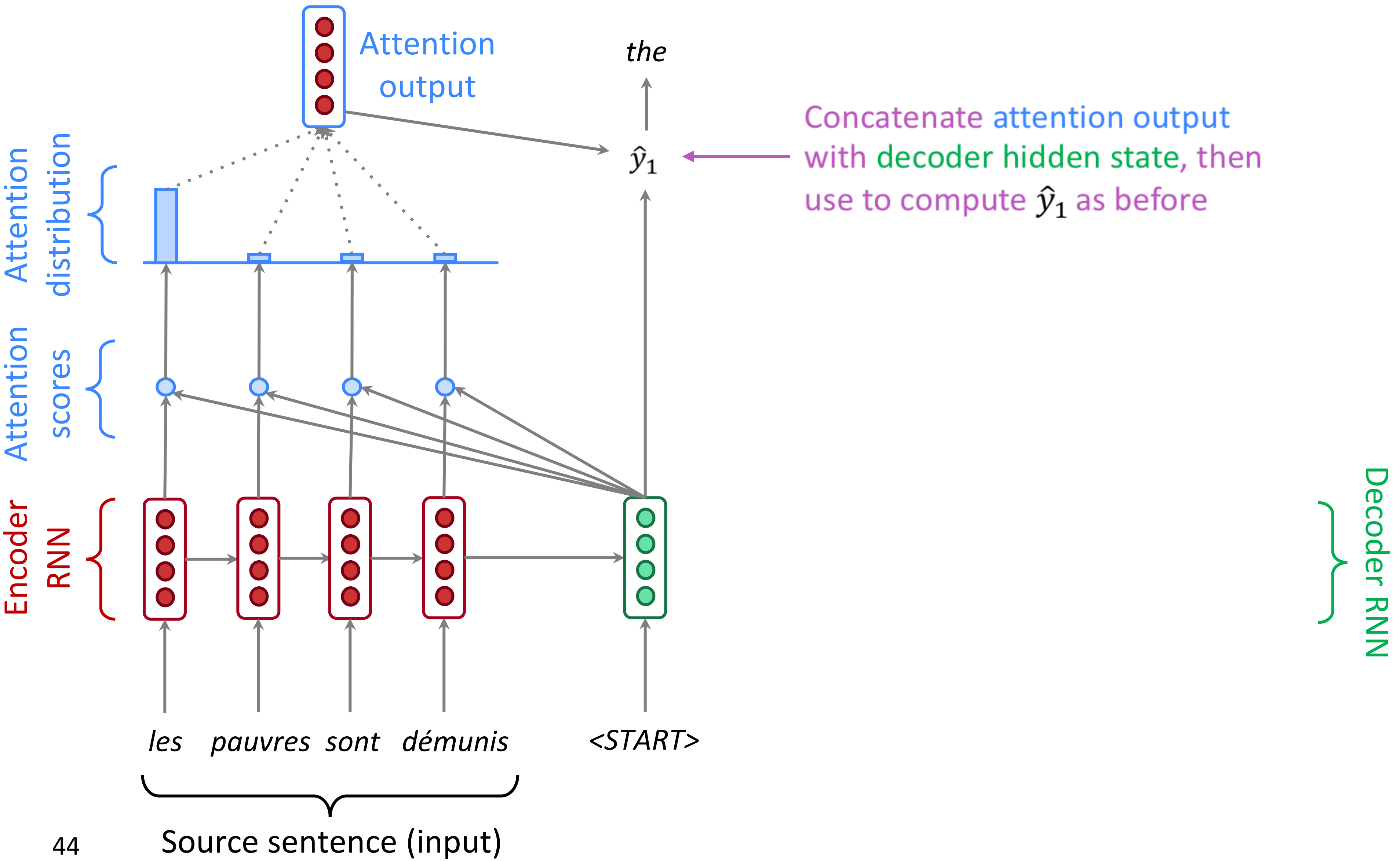
Sequence-to-sequence with attention



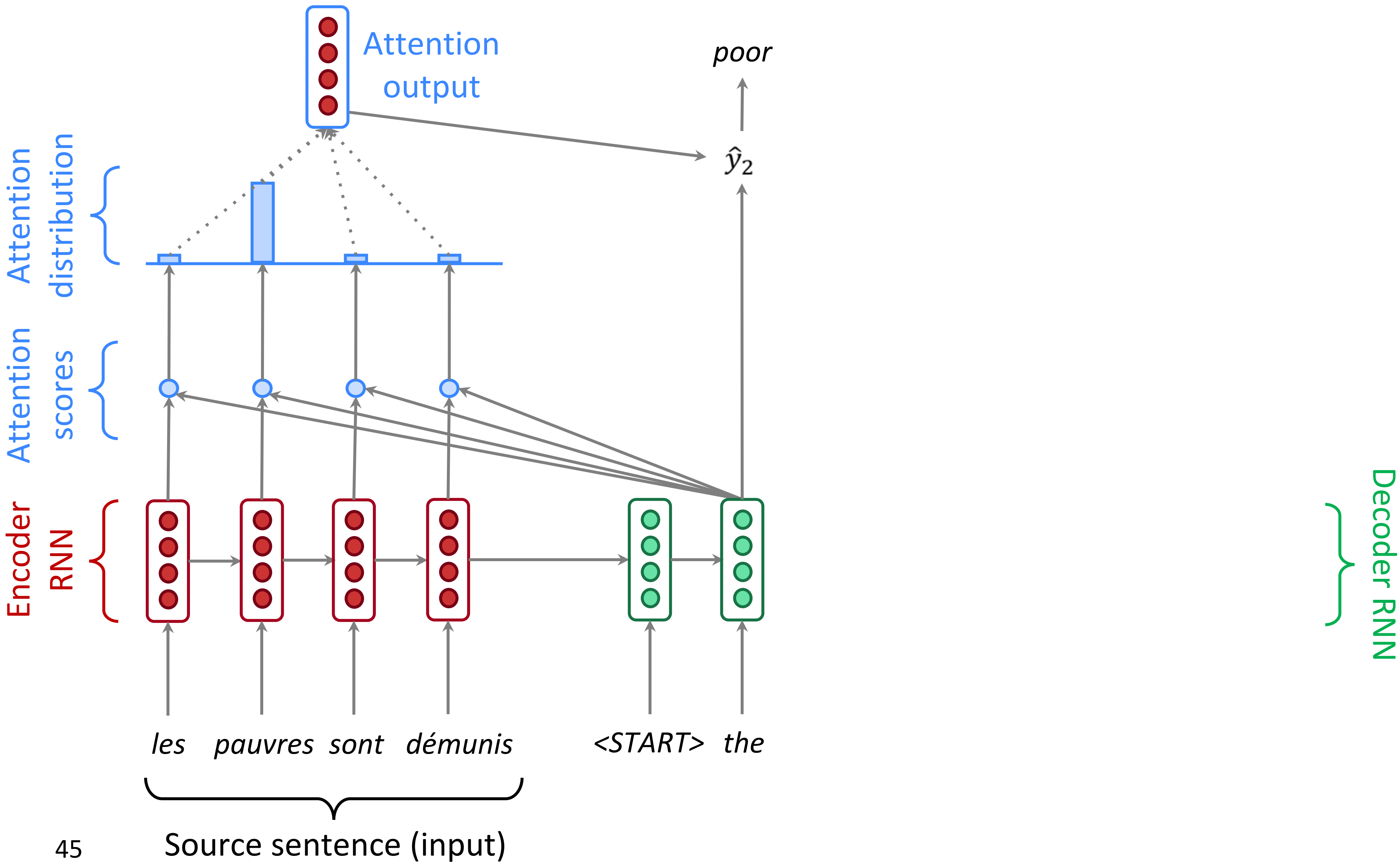
Use the attention distribution to take a **weighted sum** of the encoder hidden states.

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

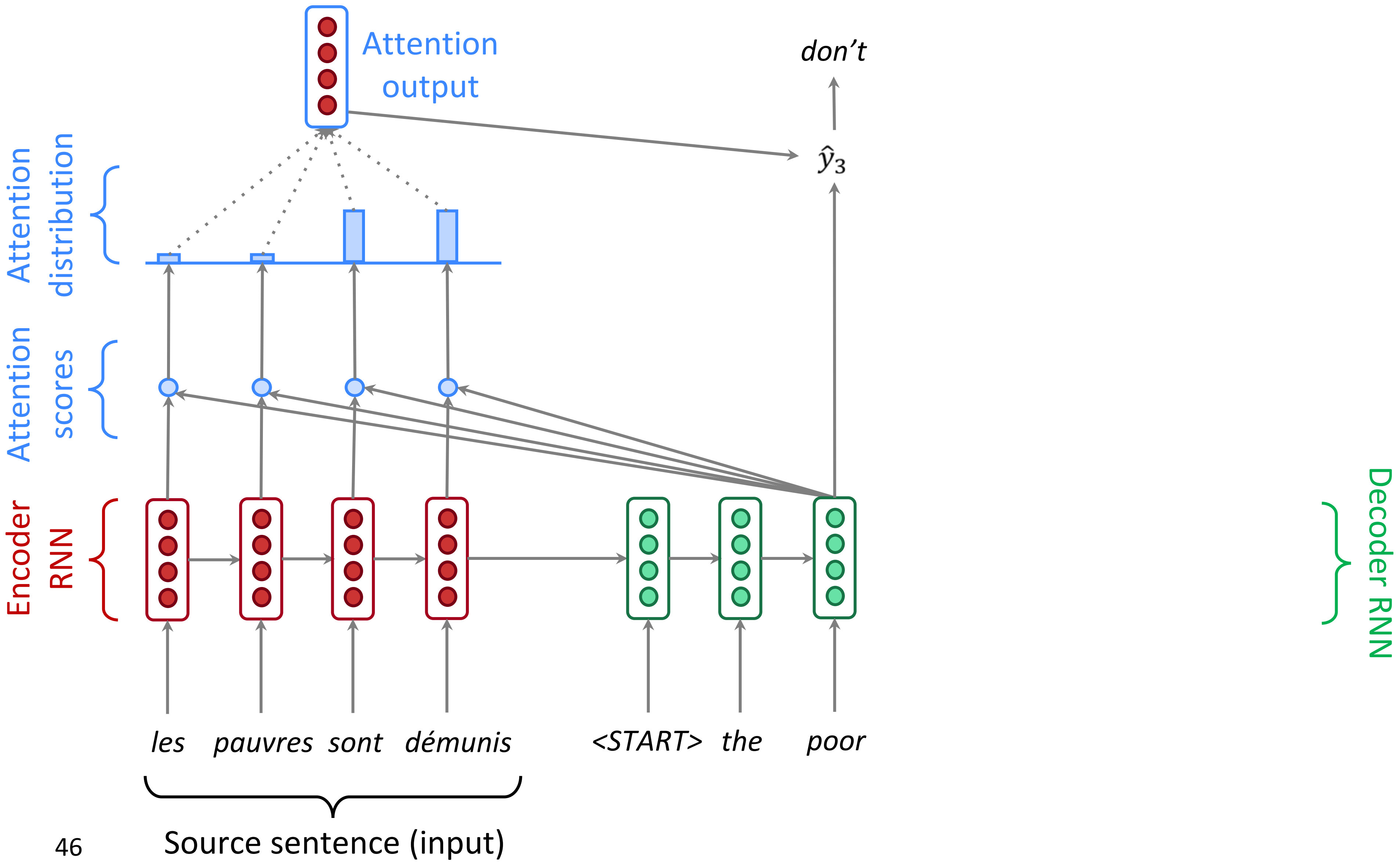
Sequence-to-sequence with attention



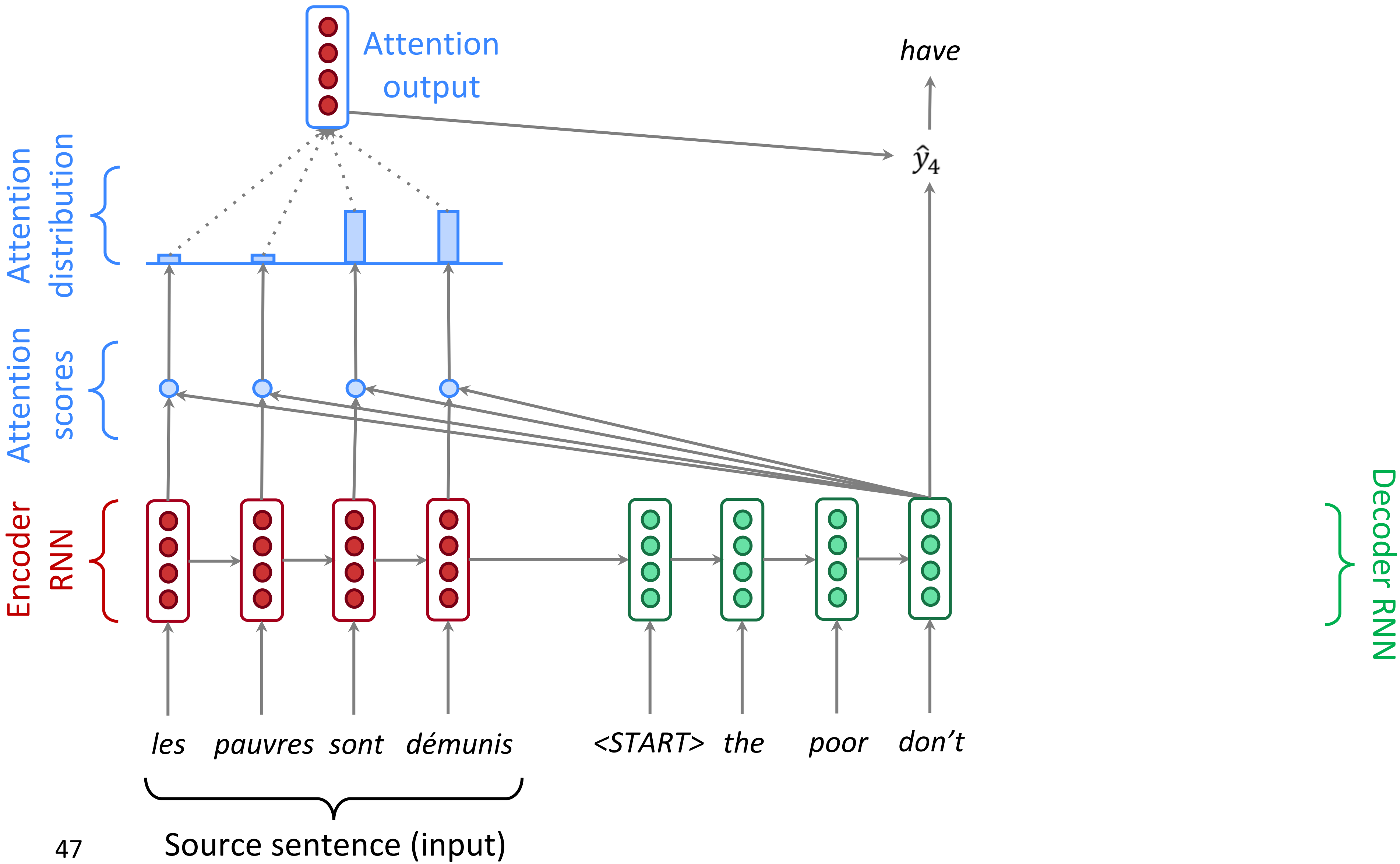
Sequence-to-sequence with attention



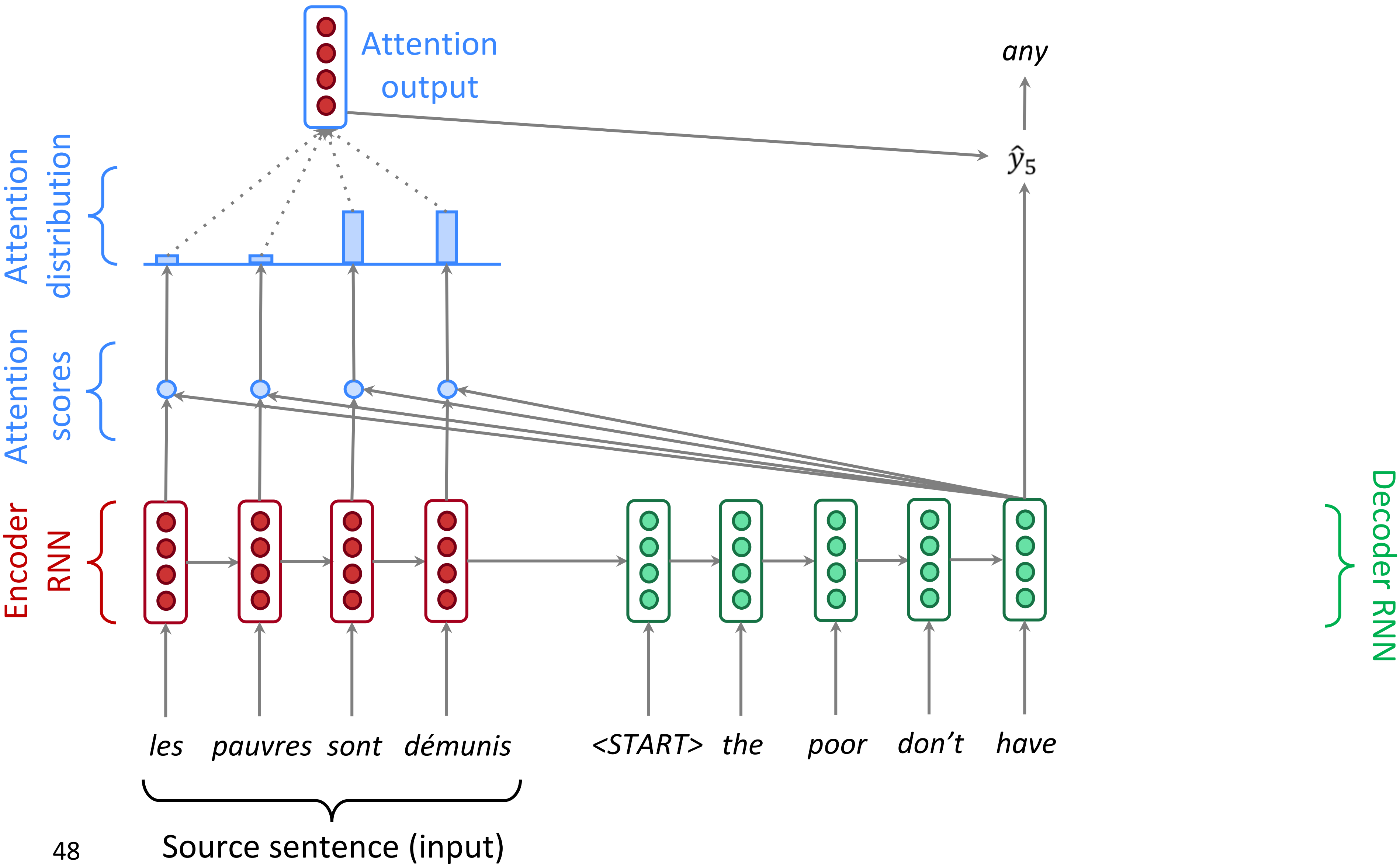
Sequence-to-sequence with attention



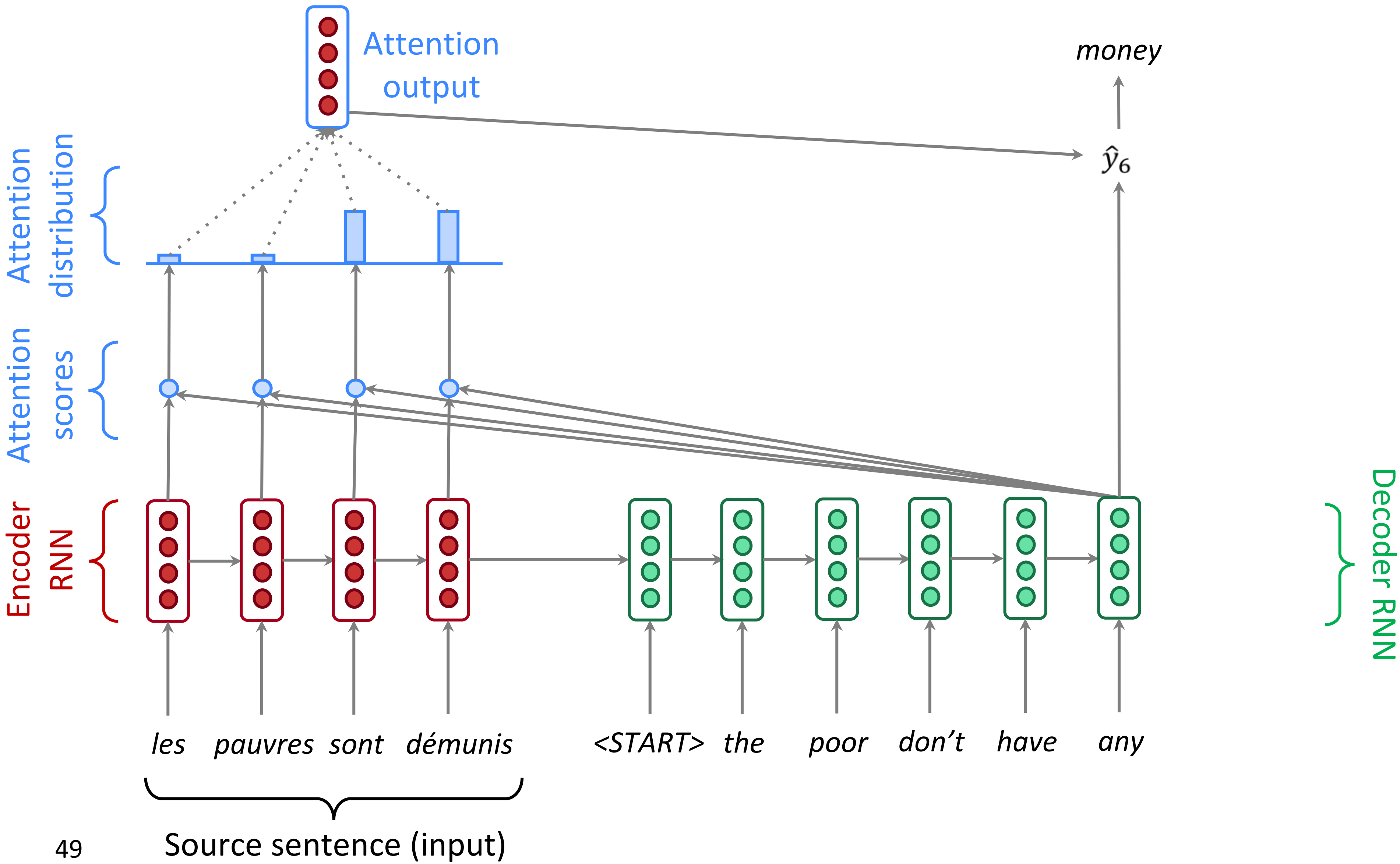
Sequence-to-sequence with attention



Sequence-to-sequence with attention



Sequence-to-sequence with attention



Attention: Công thức

- We have encoder hidden states $h_1, \ldots, h_N \in \mathbb{R}^h$
- 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:

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

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

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

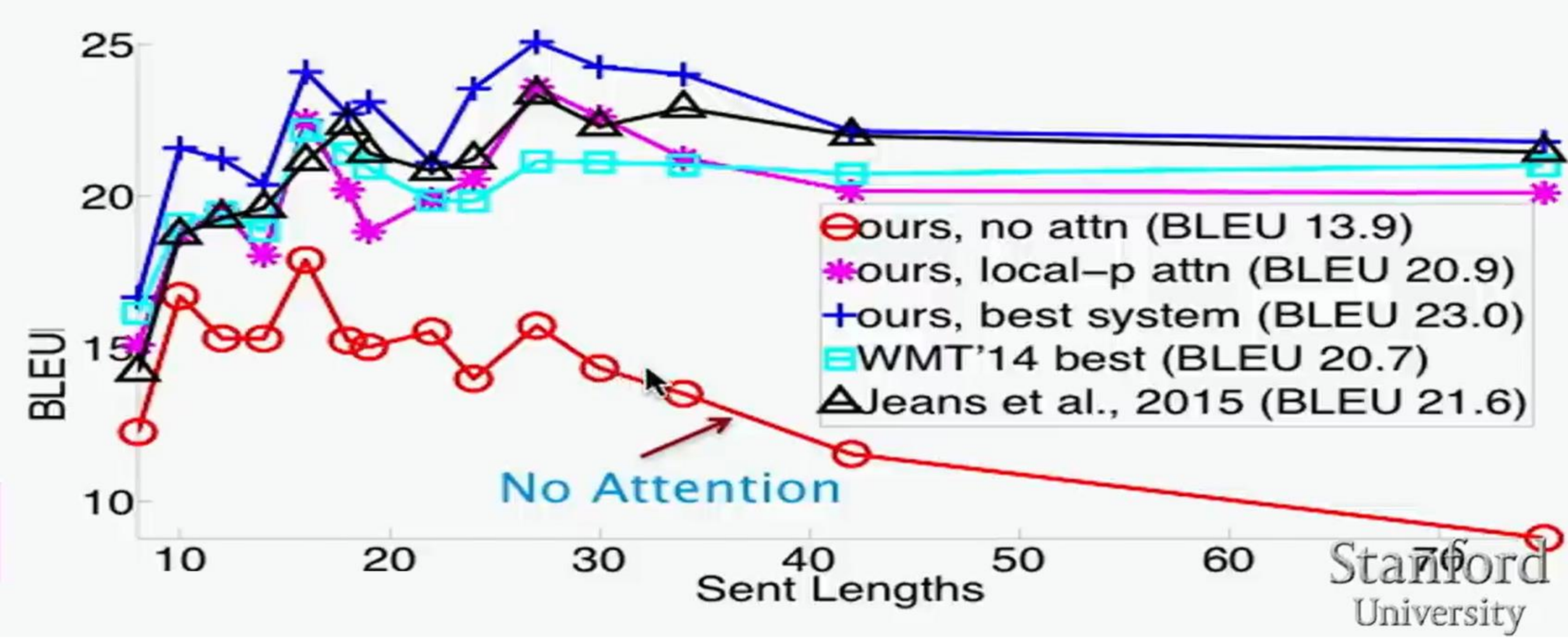
- We use α^t to take a weighted sum of the encoder hidden states to get the attention output $\boldsymbol{a}_t$

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

- 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

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

Attention dịch tốt các câu dài

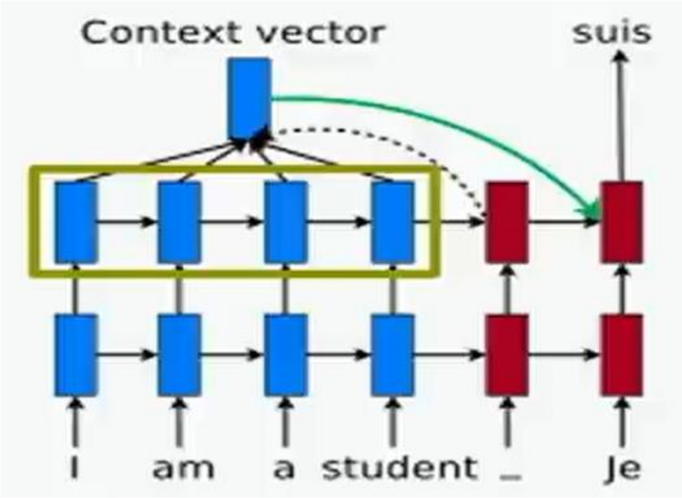


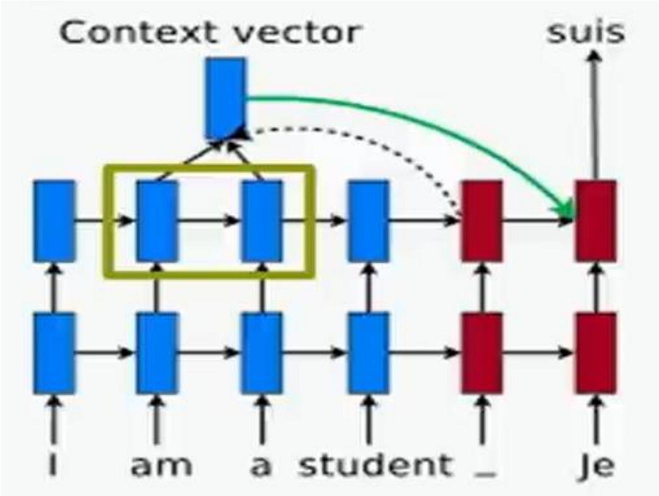
Dịch từ tiếng Anh sang tiếng Đức

source	Orlando Bloom and *Miranda Kerr* still love each other
human	Orlando Bloom und **Miranda Kerr** lieben sich noch immer
+attn	Orlando Bloom und $\boxed{\textbf{Miranda Kerr}}$ lieben einander noch immer .
base	Orlando Bloom und $\boxed{\textbf{Lucas Miranda}}$ lieben einander noch immer .

Global vs. Local Attention

- Tránh chú ý đến mọi thứ



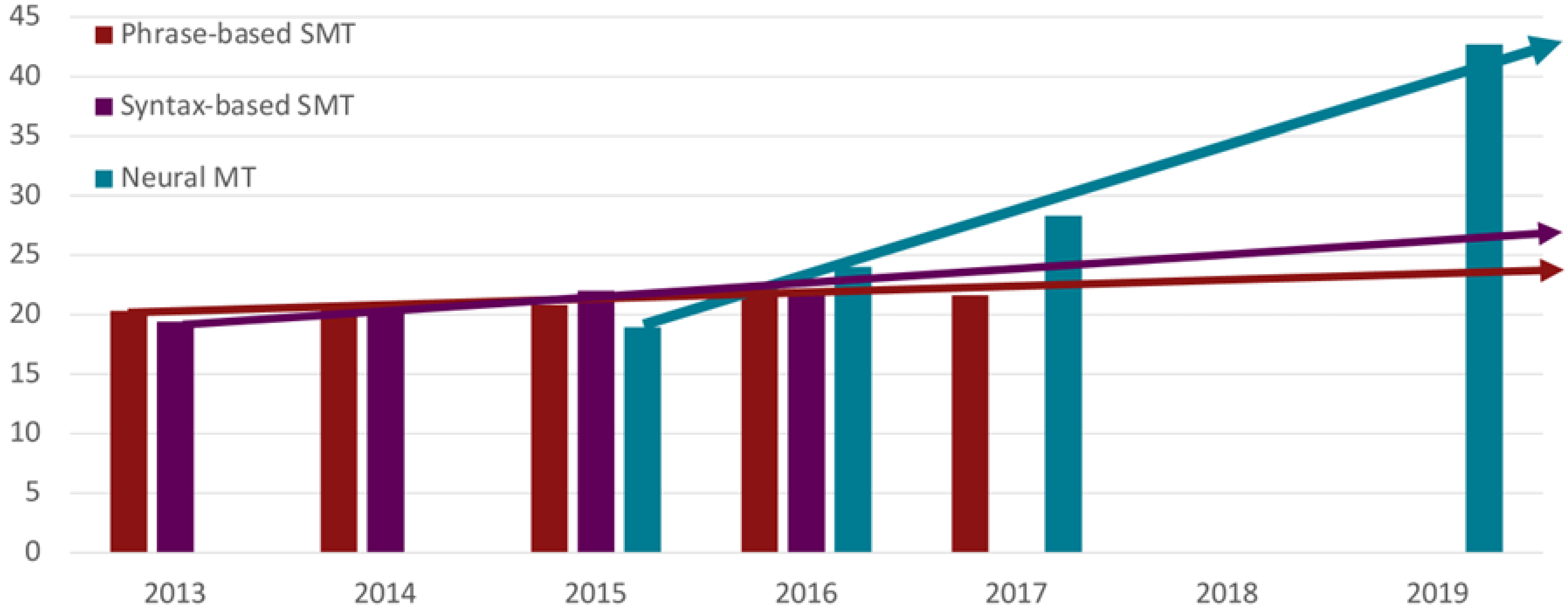


Global: all source states

Local: subset of source states

Tiến triển của hệ thống MT theo thời gian

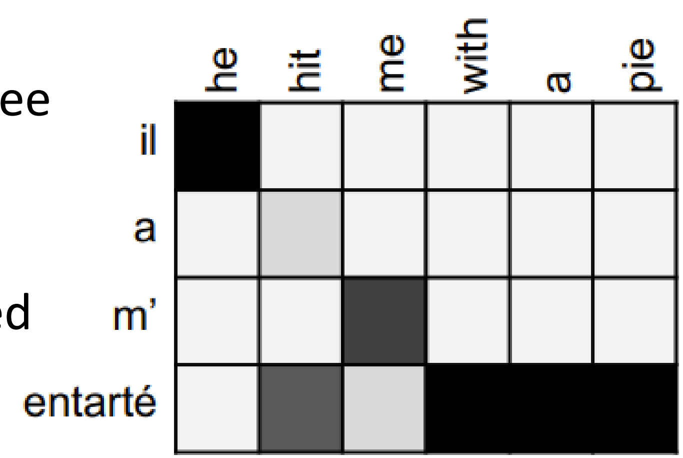
[Edinburgh En-De WMT newstest2013 Cased BLEU; NMT 2015 from U. Montréal; NMT 2019 FAIR on newstest2019]



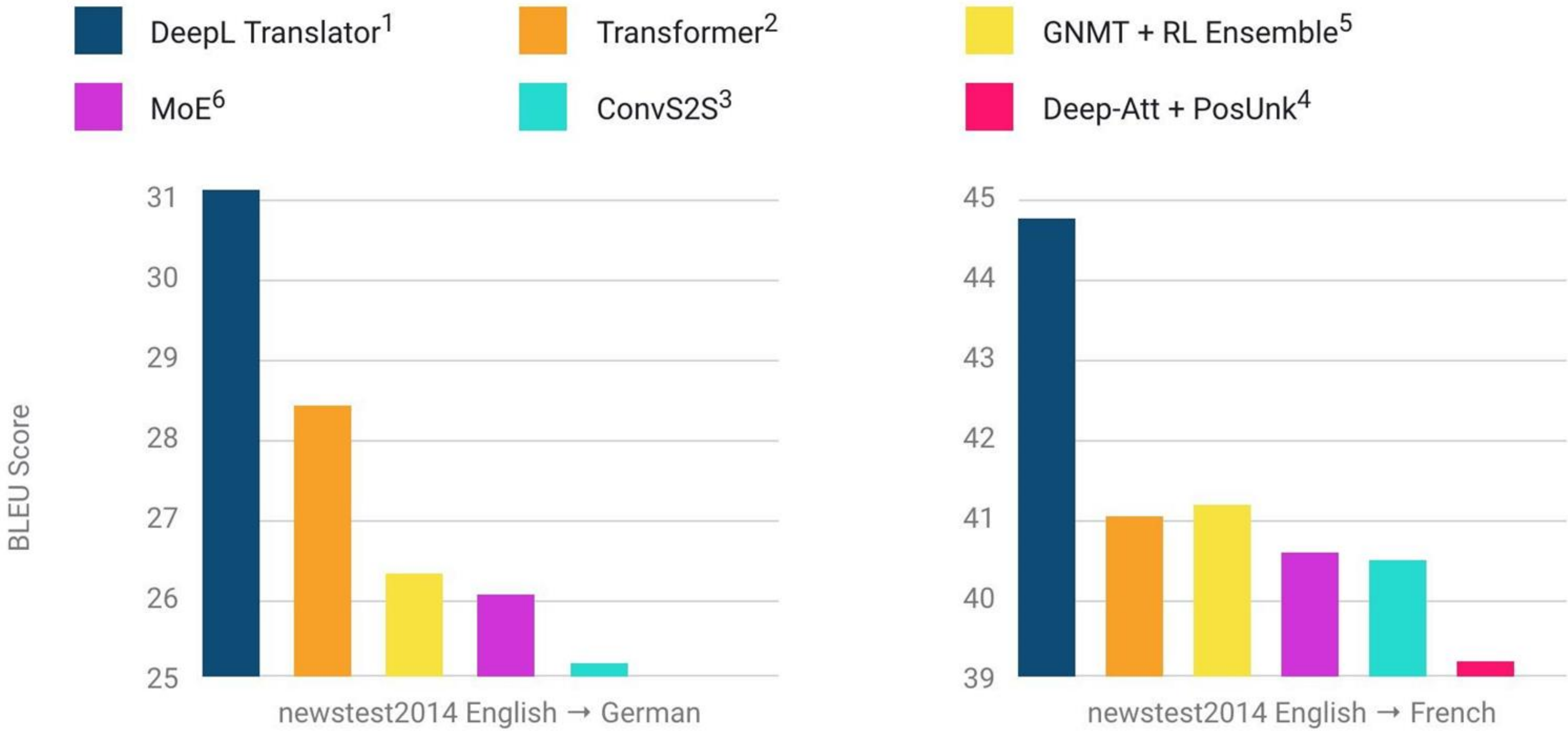
Source: Neural Machine Translation: Breaking the Performance Plateau (meta-net.eu)

Attention tuyệt vời (Bahdanau at al., 14164 citations)

- Attention significantly improves NMT performance
  - It’s very useful to allow decoder to focus on certain parts of the source
- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides shortcut to faraway states
- Attention provides some interpretability
  - By inspecting attention distribution, we can see what the decoder was focusing on
  - We get alignment for free!
  - This is cool because we never explicitly trained an alignment system
  - The network just learned alignment by itself



Data data data



Source: DeepL's press release (Aug 2017)

NMT: Câu chuyện thành công lớn nhất của NLP Deep Learning

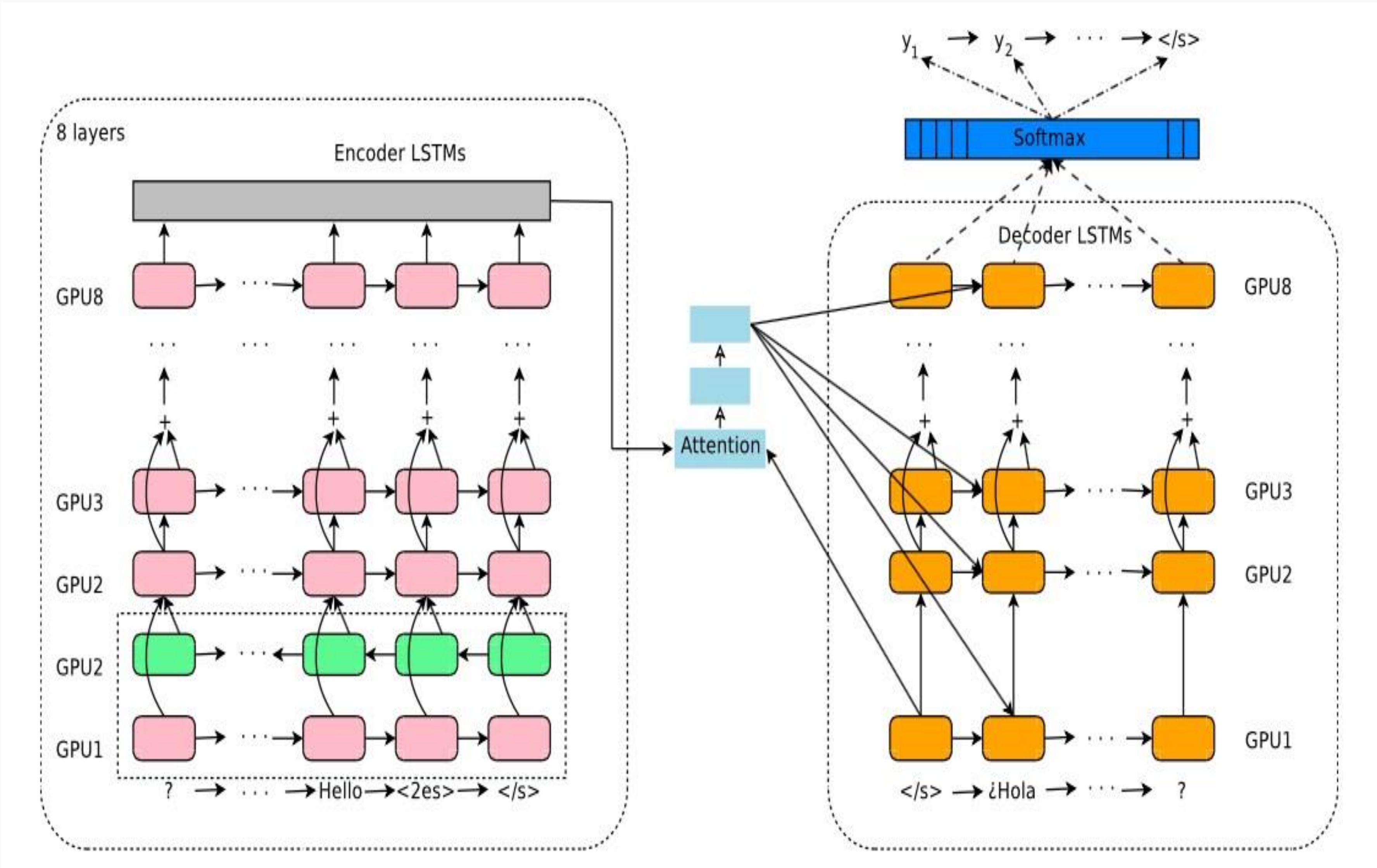
Neural Machine Translation went from a fringe research activity in **2014** to the leading standard method in **2016**

- **2014**: First seq2seq paper published
- **2016**: Google Translate switches from SMT to NMT
- This is amazing!
  - **SMT** systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a handful of engineers in a few months

Vậy là MT đã được giải quyết chưa?

- **Nope!**
- Many difficulties remain:
  - Out-of-vocabulary words
  - Domain mismatch between train and test data
  - Maintaining context over longer text
  - Low-resource language pairs

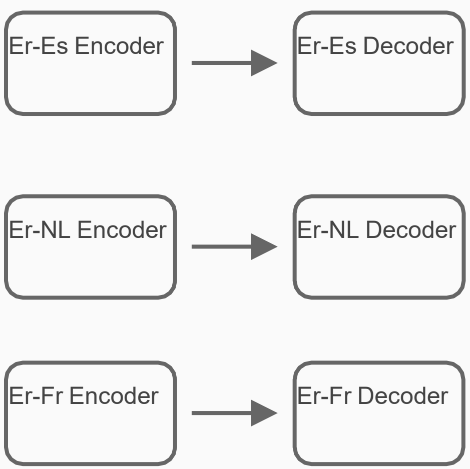
Yonghui Wu et al. (2016). Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation



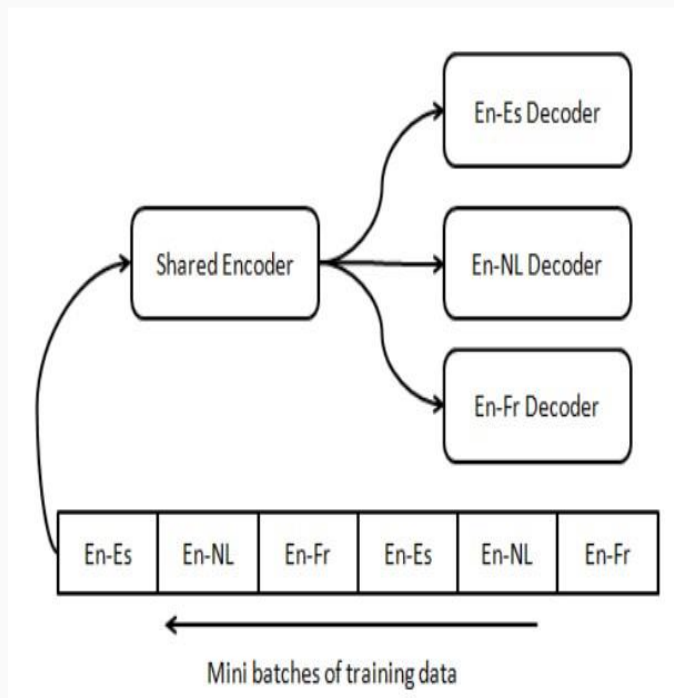
Google’s Multilingual NMT System: Enabling Zero-Shot Translation.

Melvin Johnson, Mike Schuster, Quoc V. Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat,Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, Jeffrey Dean

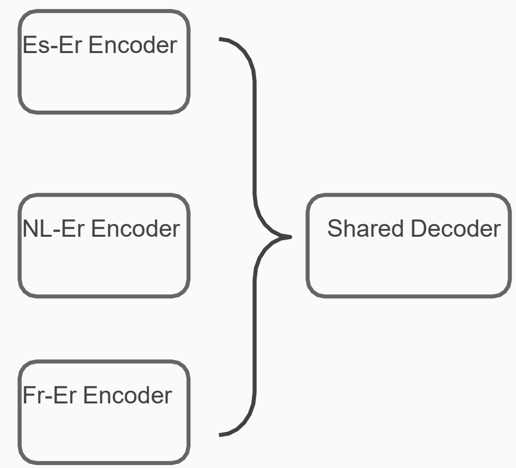
Multiple Encoders → Multiple Decoders [1]



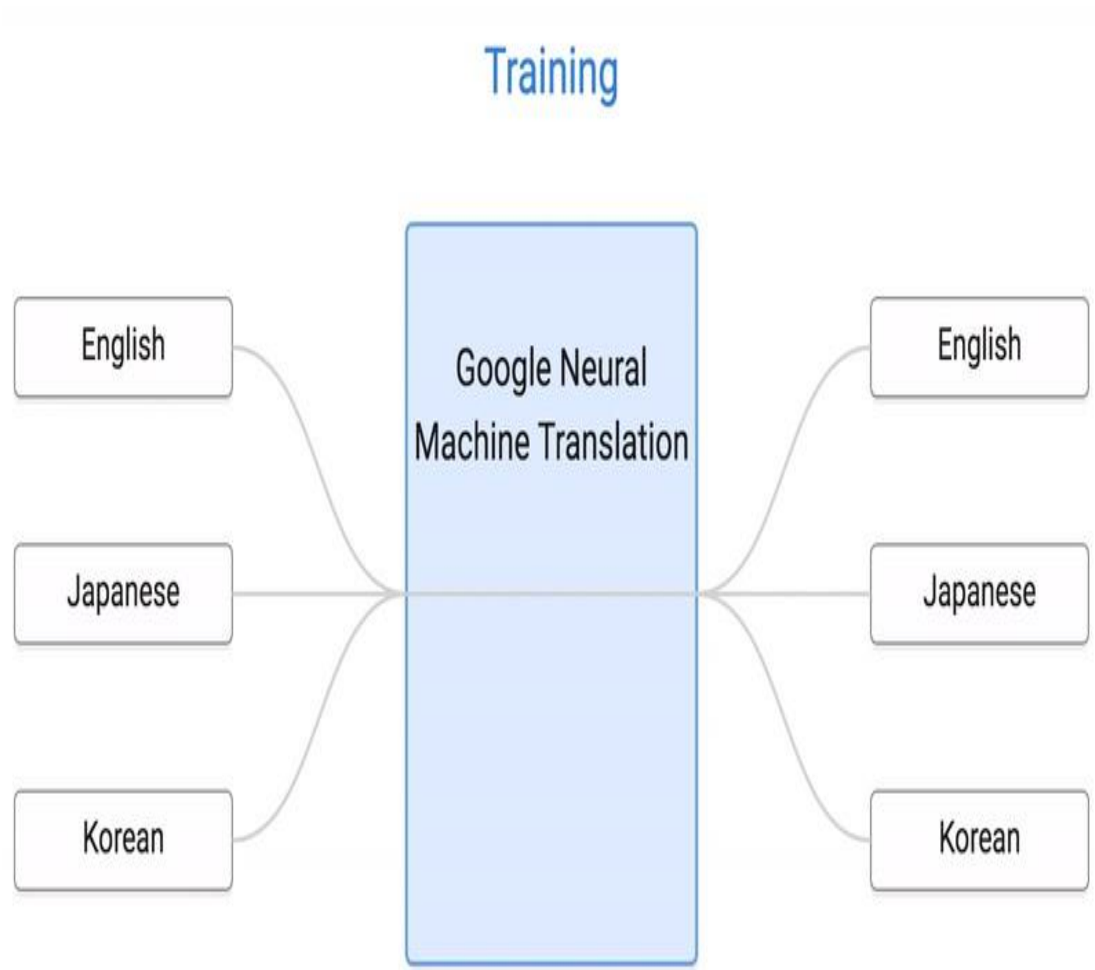
Shared Encoder → Multiple Decoder [2]



Multiple Encoders → Shared Decoder [3]



Google’s Multilingual NMT System Benefits



- **Simplicity**: single model
- **Low-resource language improvements**
- **Zero-shot translation**

Google’s Multilingual NMT System Architecture

Artificial token at the beginning of the input sentence to indicate the target language

Hello, how are you? -> ¿Hola como estás?

Add <2es> to indicate that
Spanish is the target language

<2es> Hello, how are you? -> ¿Hola como estás?

Google's Multilingual NMT System Experiments

- WMT'14:
  - Comparable performance: English → French
  - State-of-the-art: English → German, French → English
- WMT'15:
  - State-of-the-art: German → English

Google's Multilingual NMT System Zero-Shot Translation

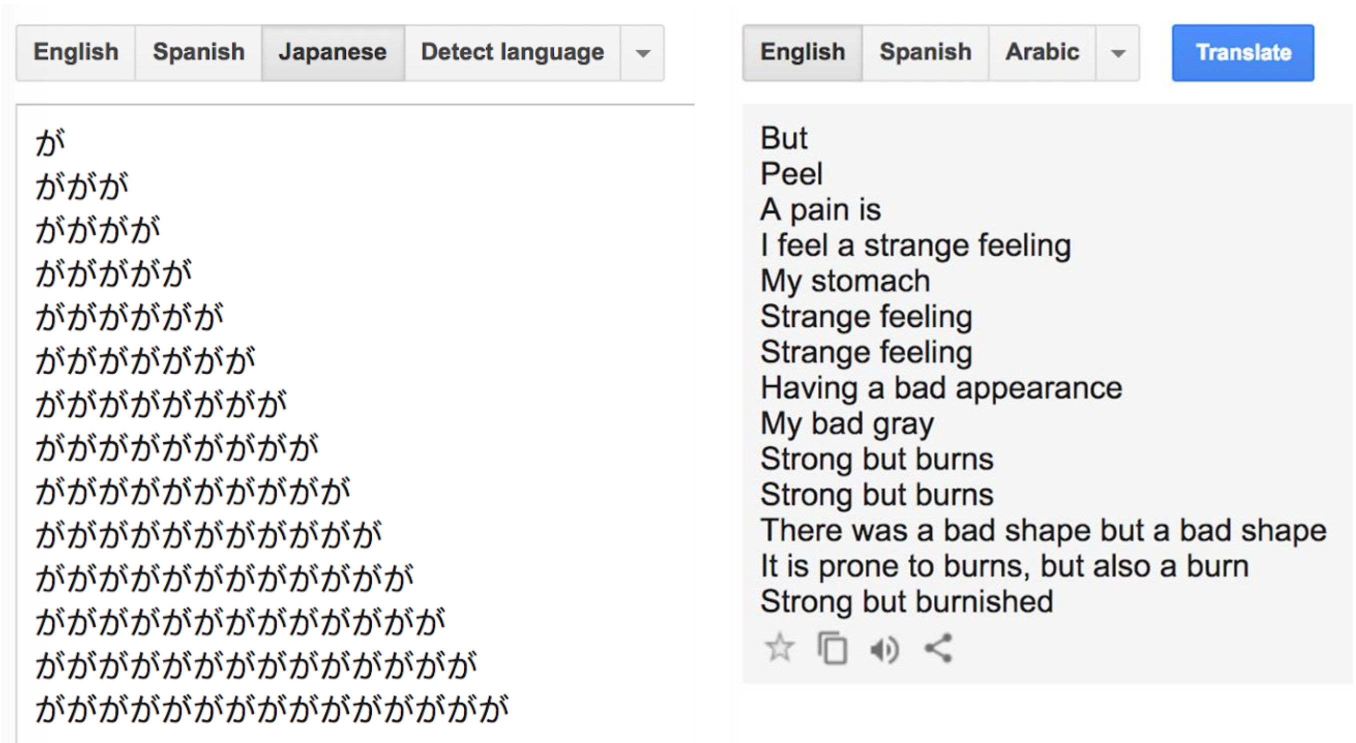
Table 5: Portuguese→Spanish BLEU scores using various models.

	Model	BLEU
(a)	PBMT bridged	28.99
(b)	NMT bridged	30.91
(c)	NMT Pt→Es	31.50
(d)	Model 1 (Pt→En, En→Es)	21.62
(e)	Model 2 (En↔{Es, Pt})	24.75
(f)	Model 2 + incremental training	31.77

- **Train**:
  - Portuguese → English, English → Spanish (Model 1)
  - Or, English ←→ {Portuguese, Spanish} (Model 2)
- **Test**:
  - Portuguese → Spanish **Zero-Shot!**

Vậy là MT đã được giải quyết chưa?

- Nope!
- Uninterpretable systems do strange things



Source: http://languagelog.ldc.upenn.edu/nll/?p=35120#more-35120

Seq2seq là rất linh hoạt!

- 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)

Kết luận

- Since 2014, Neural MT rapidly replaced intricate Statistical MT

- Sequence-to-sequence is the architecture for NMT (uses 2 RNNs)

- Attention is a way to *focus on particular parts* of the input
  - Improves sequence-to-sequence a lot!