CS20: TensorFlow for Deep Learning Research

Lecture 12 (2/23/2014)
Machine Translation,
Sequence-to-sequence and Attention

Slides courtesy of [CS22N]

Assignment 3

- Chat bot
- Language model
- Word vector transformation
- Project of choice

Overview

Today we will:

- Introduce a new task: Machine Translation

is the primary use-case of

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

is improved by

- Introduce a new neural technique: attention

Machine Translation

Machine Translation (MT) 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

↓

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

1950s: Early Machine Translation

Machine Translation research began in the early 1950s.

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

Source: https://youtu.be/K-HfpsHPmvw

- Systems were mostly rule-based, using a bilingual dictionary to map Russian words to their English counterparts
  - A cool by-product: Quicksort!

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 learnt separately:

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

Translation Model

Models how words and phrases should be translated.
Learnt from parallel data.

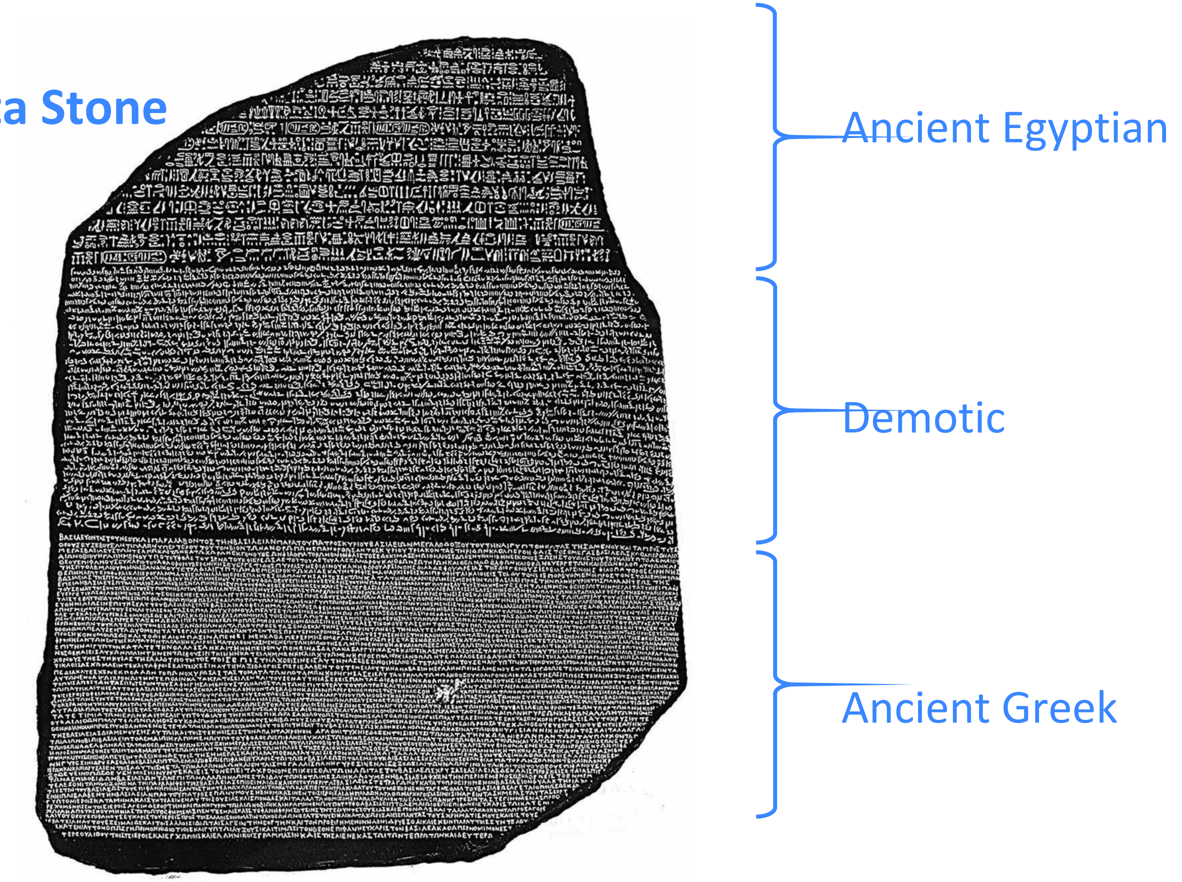
Language Model

Models how to write good English.
Learnt from monolingual data.

1990s-2010s: Statistical Machine Translation

- Question: How to learn translation model $P(x|y)$?
- First, need large amount of parallel data
  (e.g. pairs of human-translated French/English sentences)

The Rosetta Stone



1990s-2010s: Statistical Machine Translation

- Question: How to learn translation model $P(x|y)$?
- First, need large amount of parallel data
  (e.g. pairs of human-translated French/English sentences)

- Break it down further: we actually want to consider

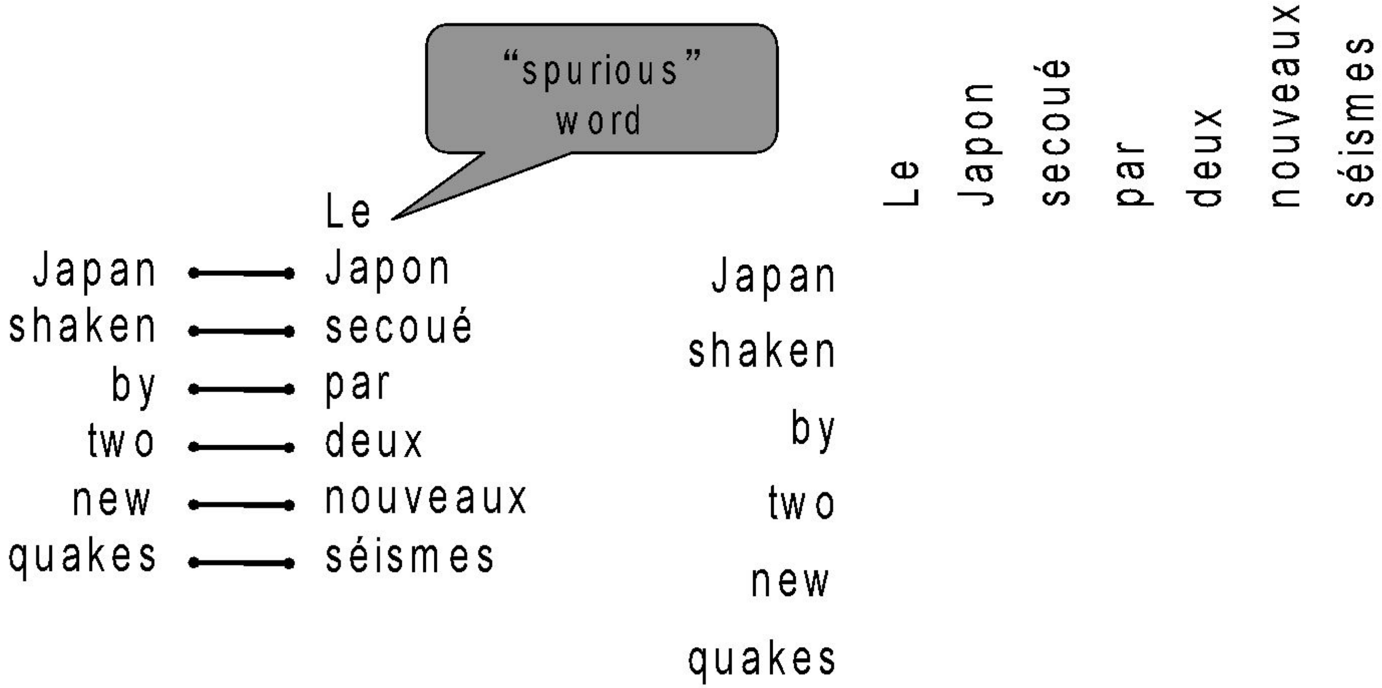
$$P(x, a|y)$$

where *a* is the alignment, i.e. word-level correspondence between French sentence *x* and English sentence *y*

What is alignment?

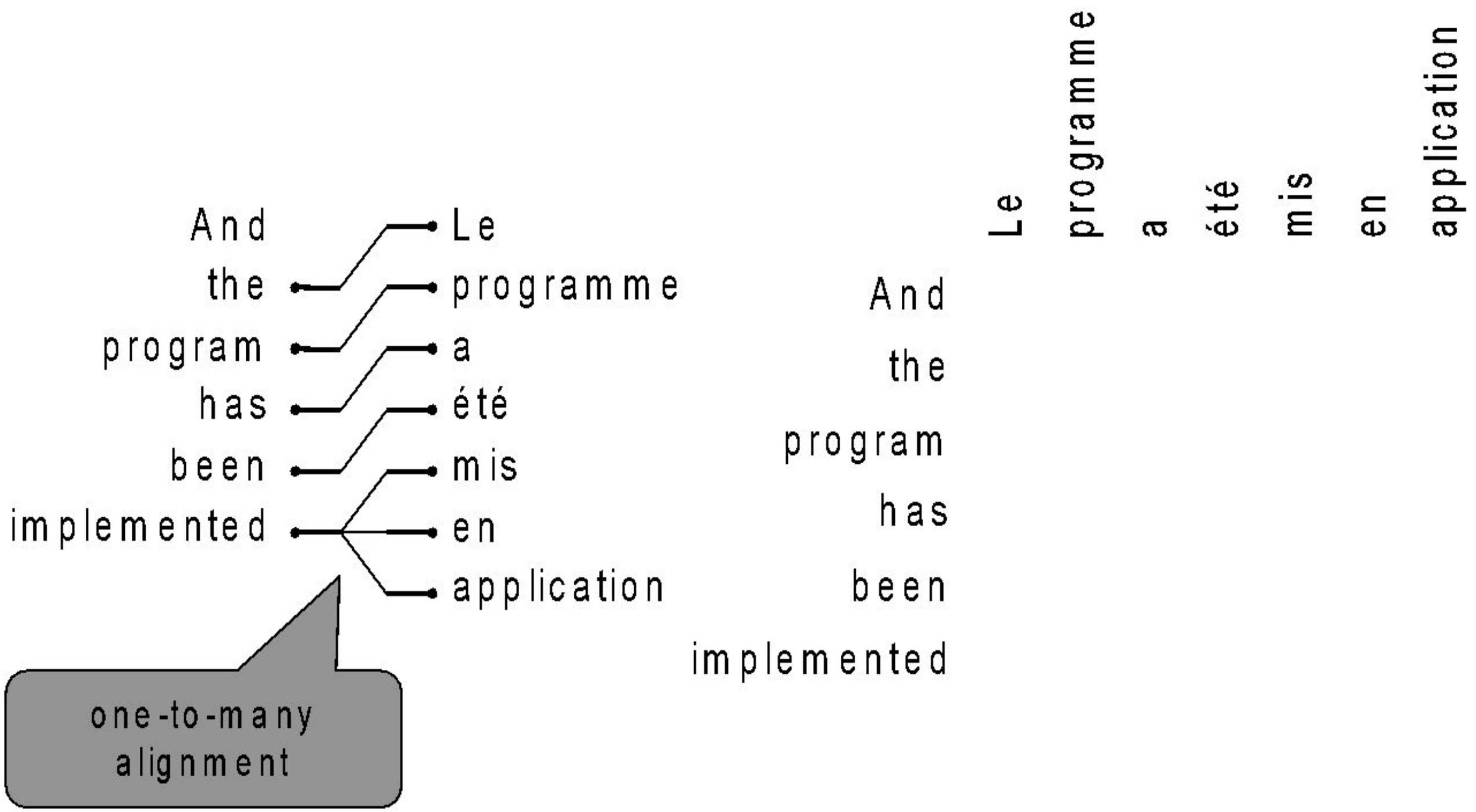
Alignment is the correspondence between particular words in the translated sentence pair.

- Note: Some words have no counterpart



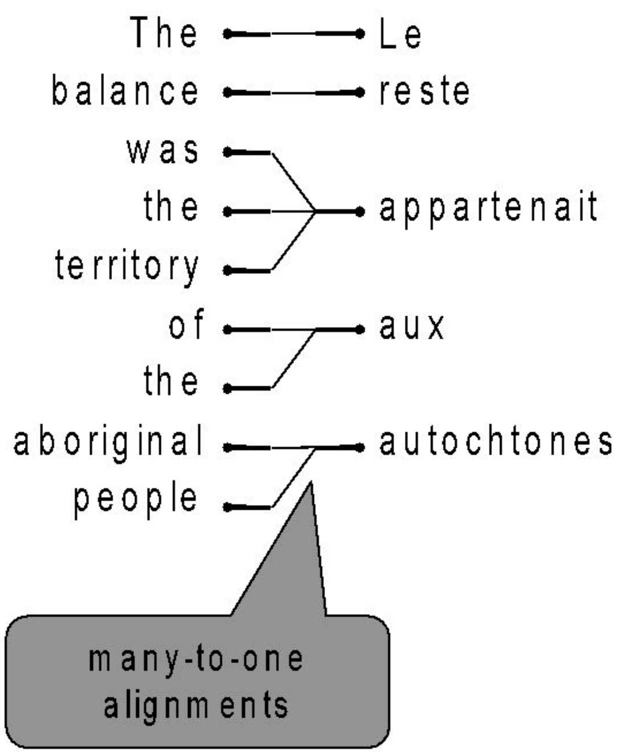
Alignment is complex

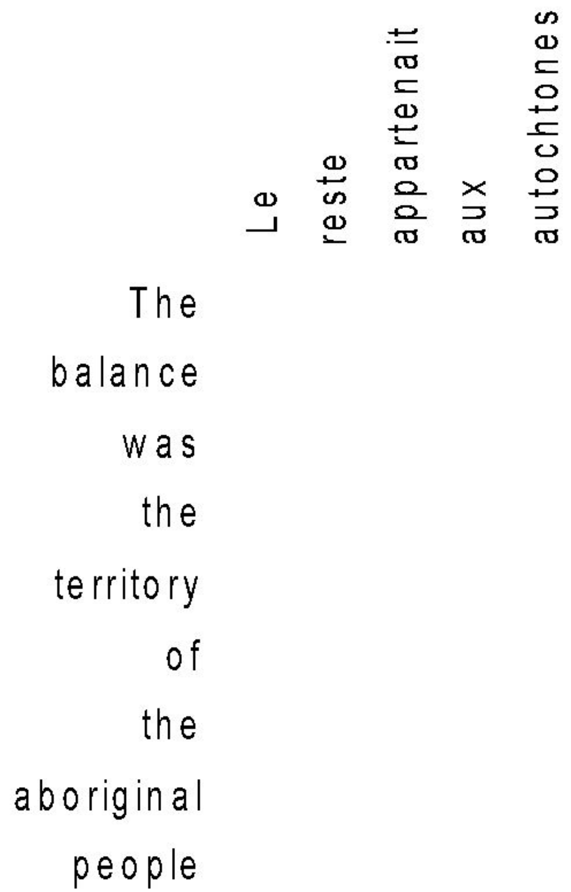
Alignment can be one-to-many (these are “fertile” words)



Alignment is complex

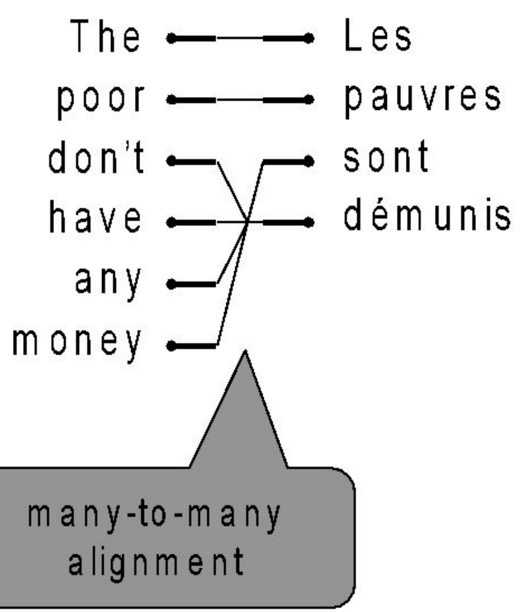
Alignment can be many-to-one

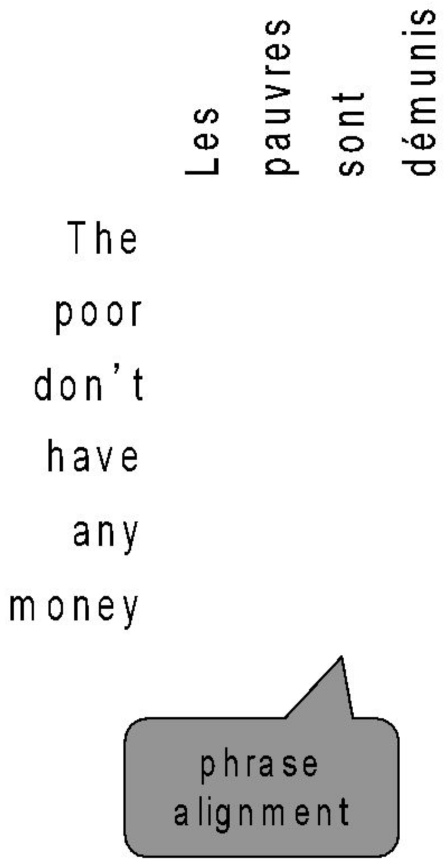




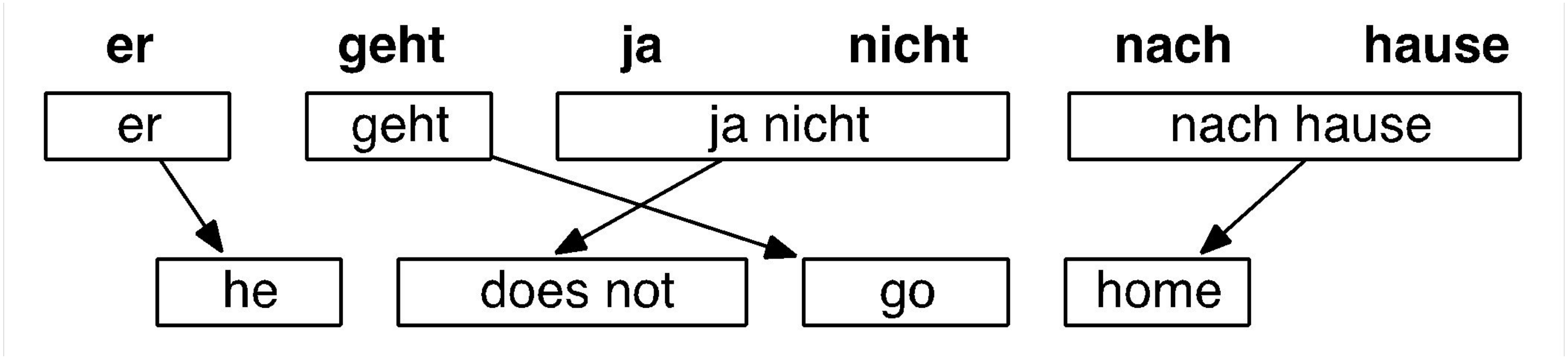
Alignment is complex

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

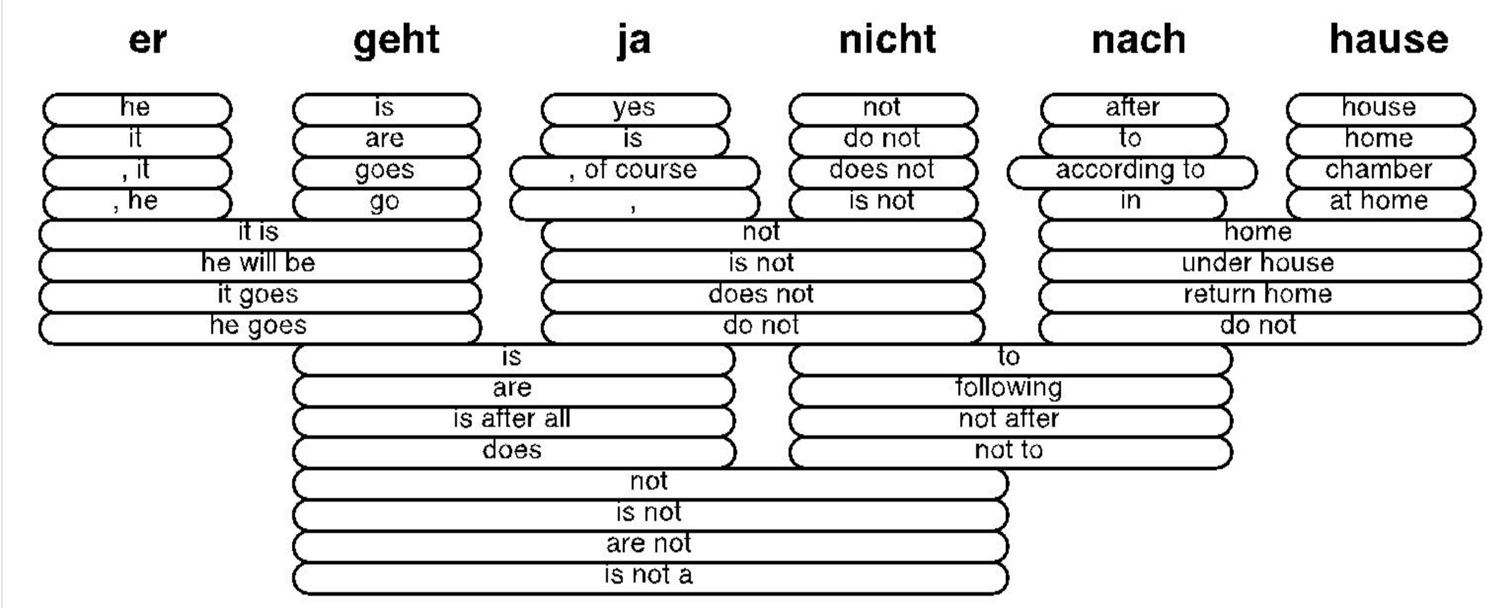


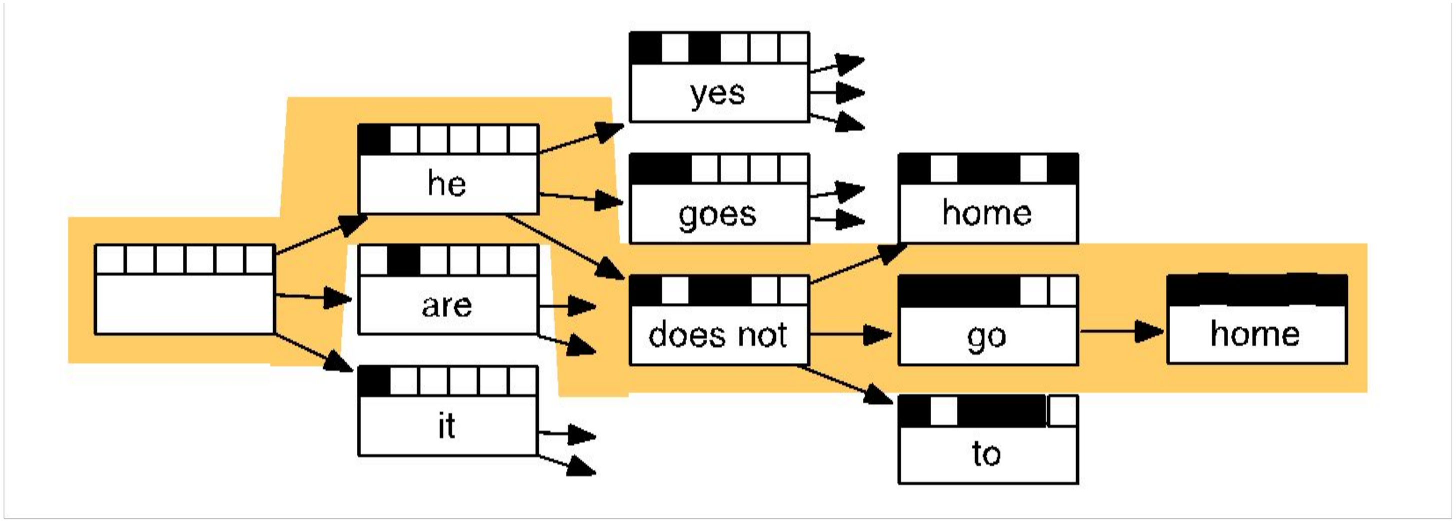


Searching for the best translation



Searching for the best translation



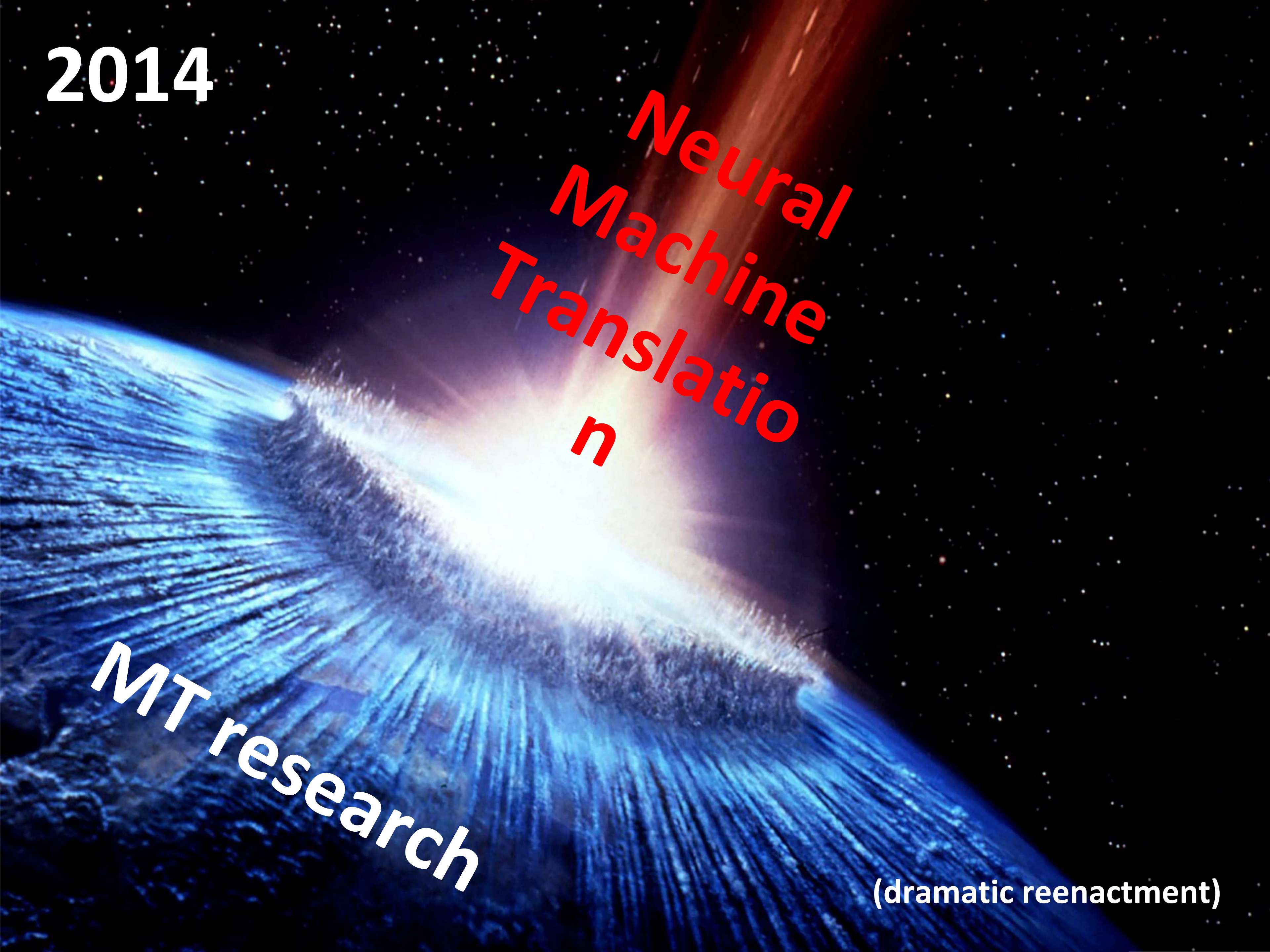


1990s-2010s: Statistical Machine Translation

- SMT is a huge research field
- The best systems are extremely complex
  - Hundreds of important details we haven't mentioned here
  - Systems have many separately-designed subcomponents
  - Lots of feature engineering
    - Need to design features to capture particular language phenomena
  - Require compiling and maintaining extra resources
    - Like tables of equivalent phrases
  - Lots of human effort to maintain
    - Repeated effort for each language pair!

2014

(dramatic reenactment)


2014
Neural Machine Translation
MT research
(dramatic reenactment)

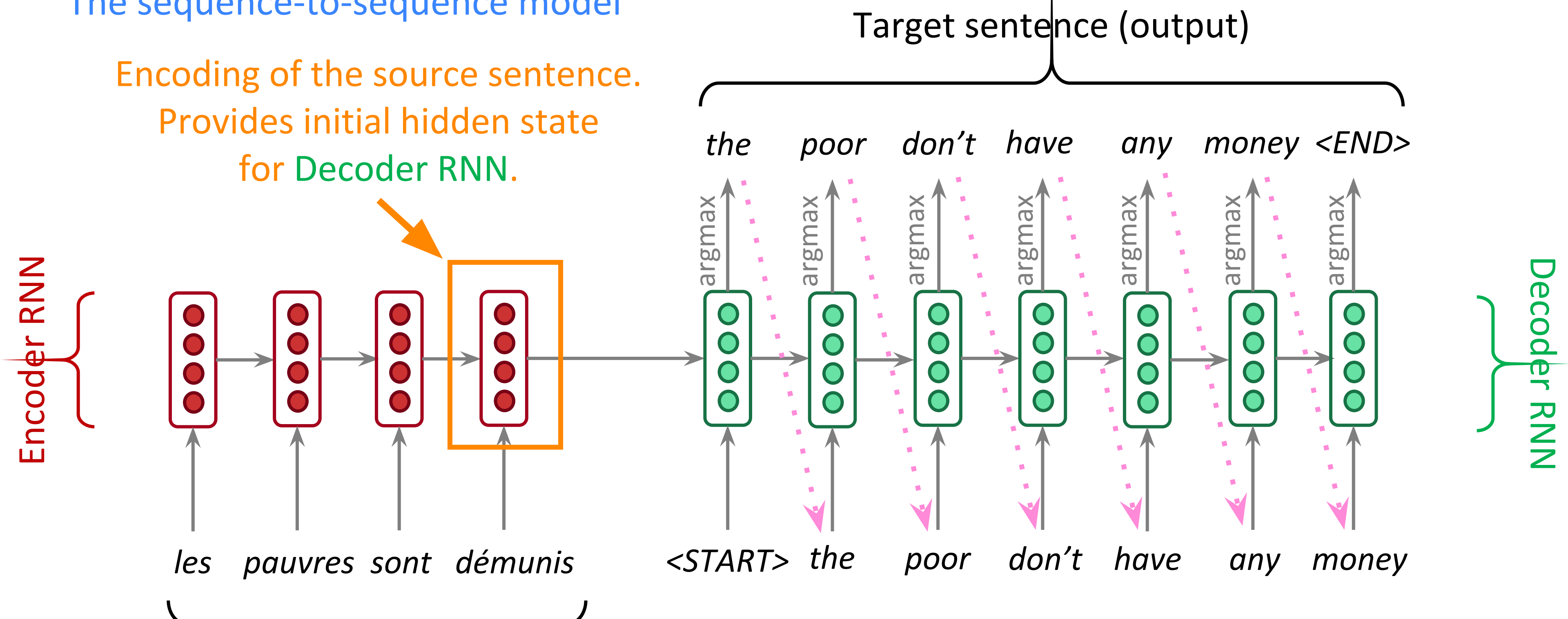
What is Neural Machine Translation?

- 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.

Neural Machine Translation (NMT)

The sequence-to-sequence model



Source sentence (input)

Encoder RNN produces an encoding of the source sentence.

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

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

Neural Machine Translation (NMT)

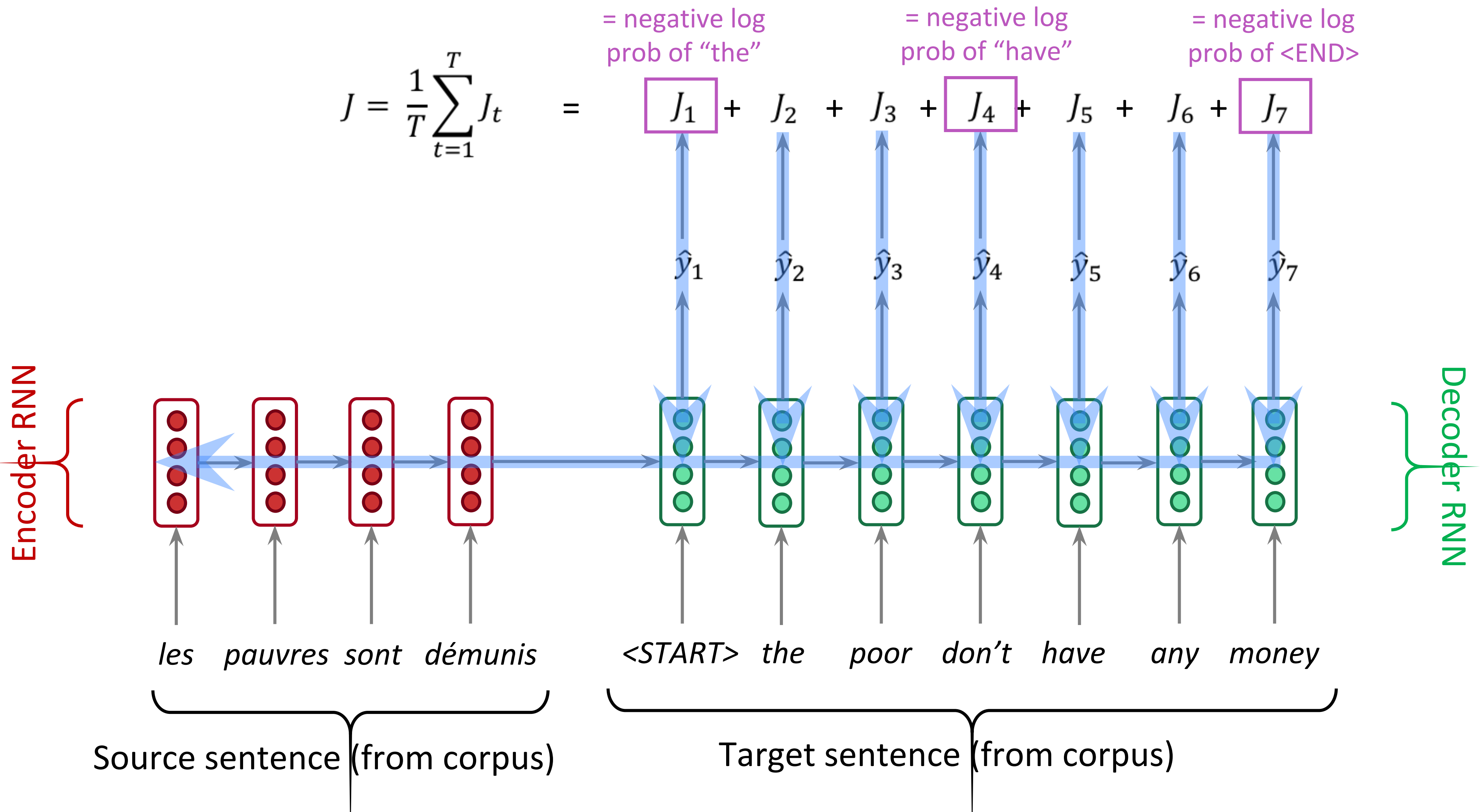
- The sequence-to-sequence model is an example of a **Conditional Language Model**.
  - **Language Model** because the decoder is predicting the next word of the target sentence *y*
  - **Conditional** because its predictions are *also* conditioned on the source sentence *x*

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

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

- **<u>Question</u>**: How to train a NMT system?
- **<u>Answer</u>**: Get a big parallel corpus…

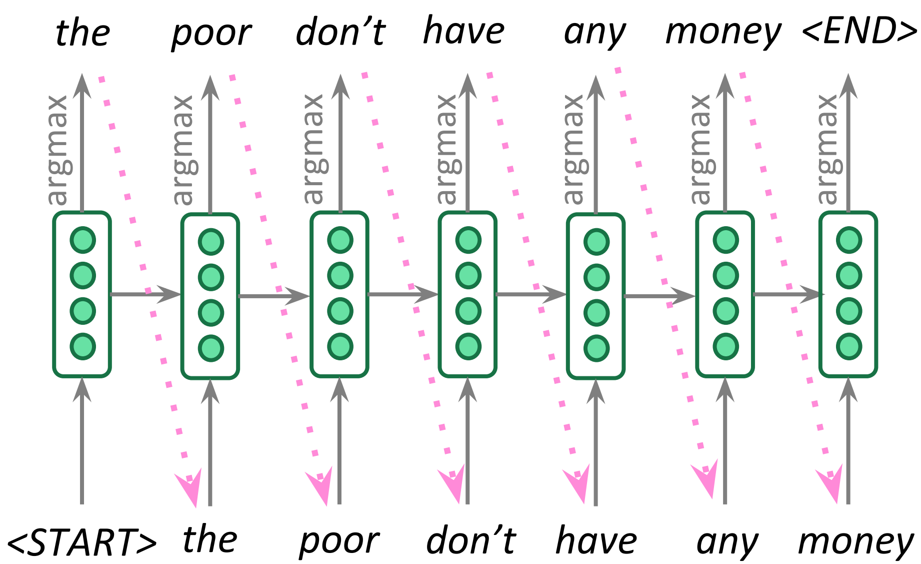
Training a Neural Machine Translation system



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

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)*
  - $\rightarrow$ *the* ____
  - $\rightarrow$ *the poor* ____
  - $\rightarrow$ *the poor are* ____

- Better option: use beam search (a search algorithm) to explore *several* hypotheses and select the best one

Beam search decoding

- 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!

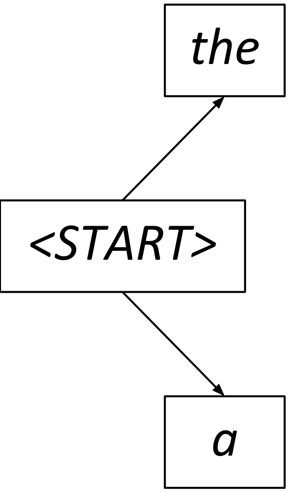
Beam search decoding: example

Beam size = 2

<START>

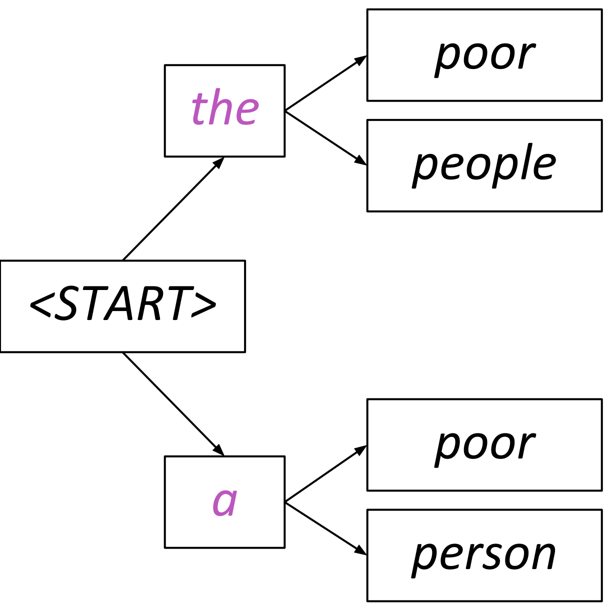
Beam search decoding: example

Beam size = 2



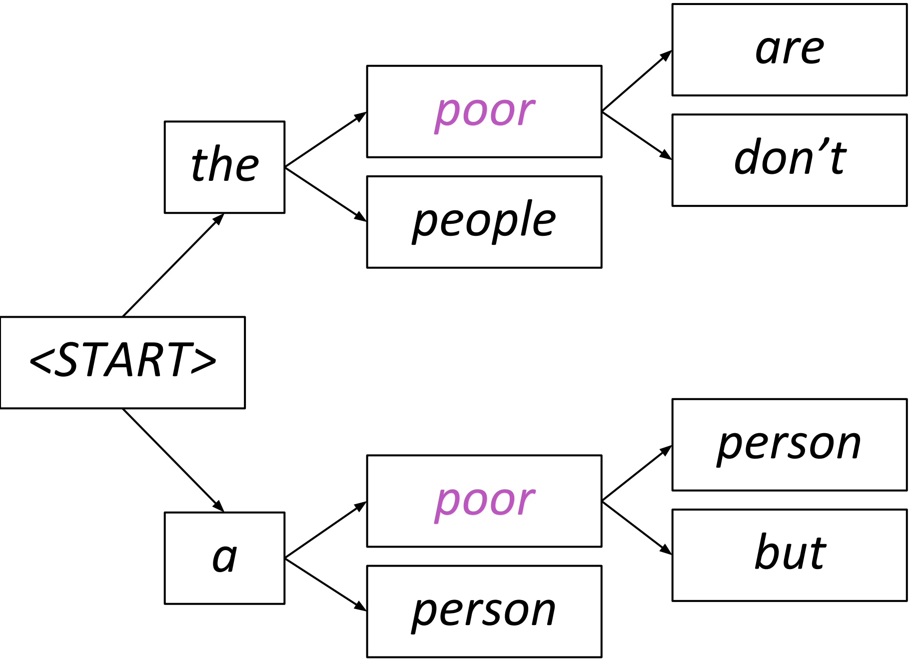
Beam search decoding: example

Beam size = 2



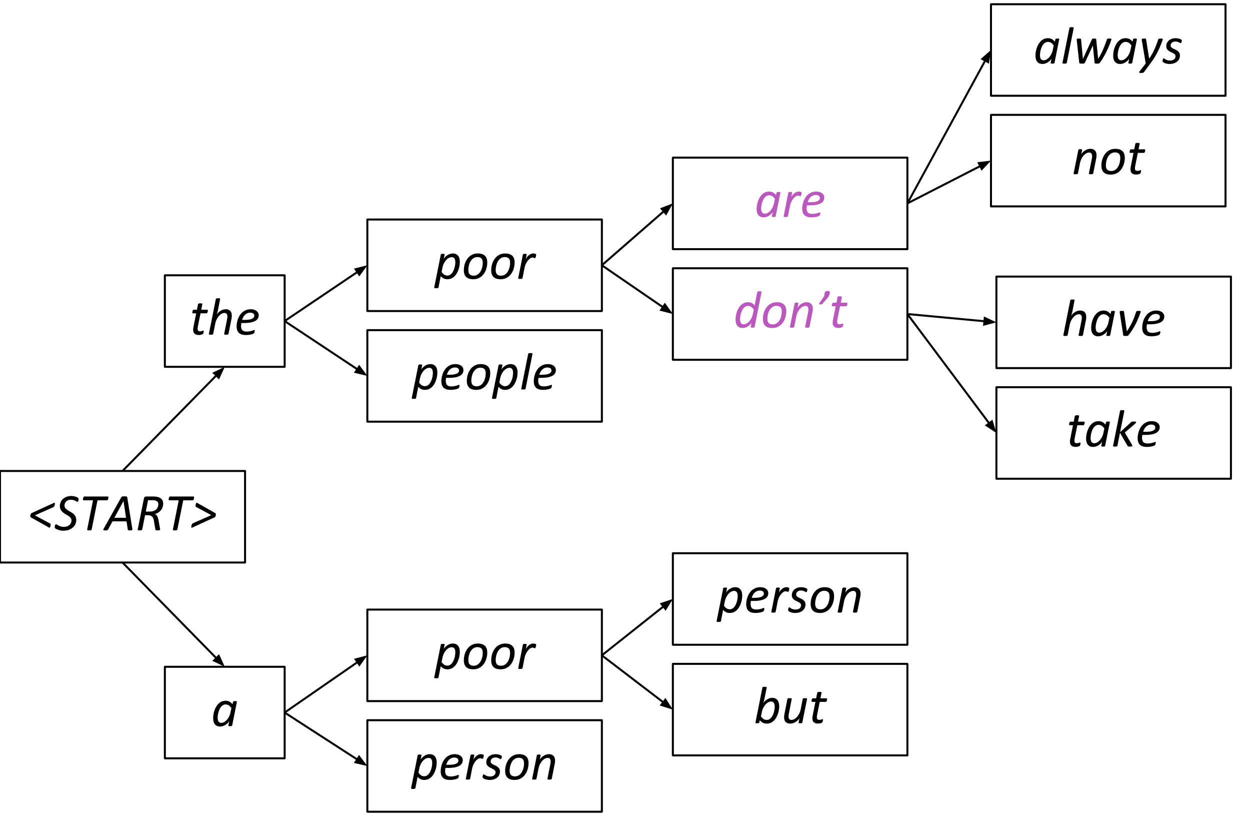
Beam search decoding: example

Beam size = 2



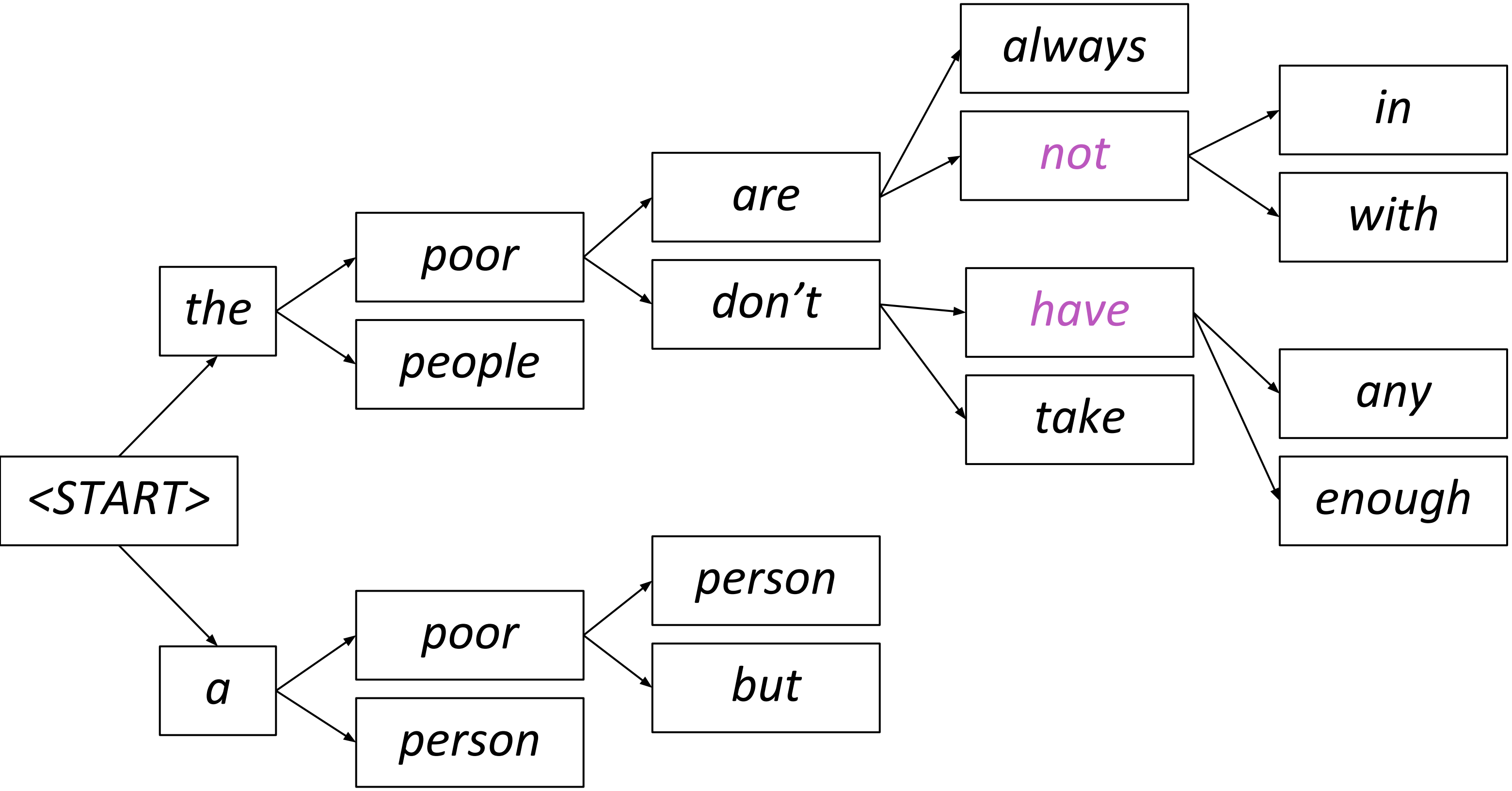
Beam search decoding: example

Beam size = 2



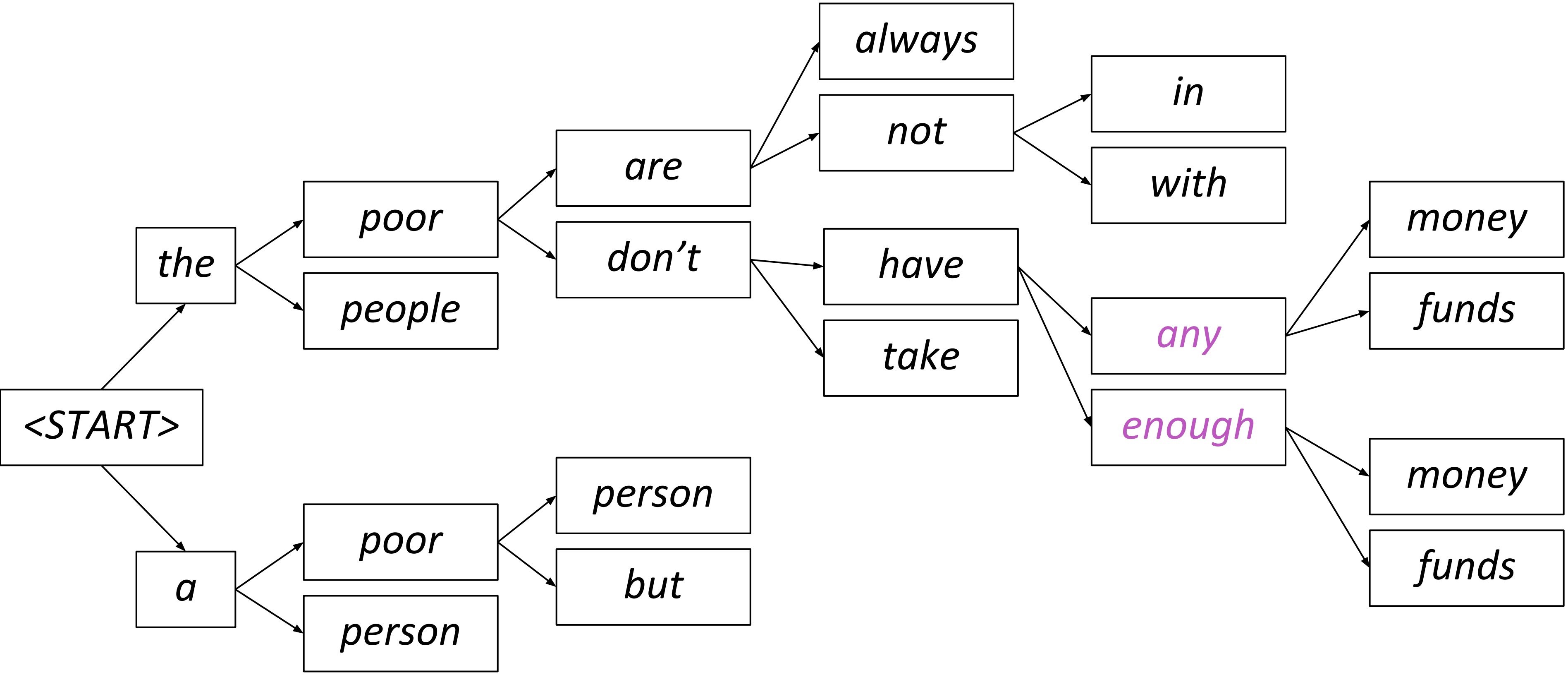
Beam search decoding: example

Beam size = 2



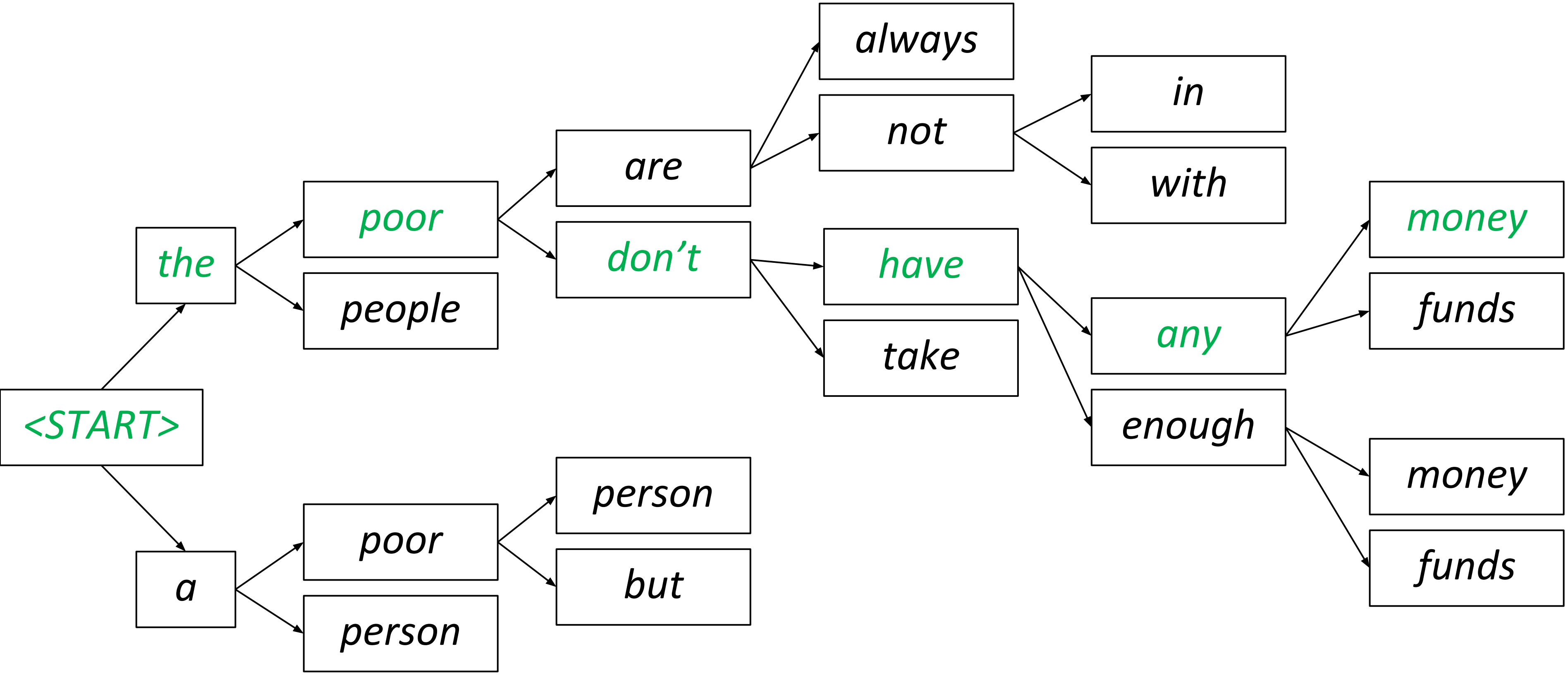
Beam search decoding: example

Beam size = 2



Beam search decoding: example

Beam size = 2



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!

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!

SMT is still very much in use!

How do we evaluate Machine Translation?

BLEU (**Bi**lingual **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

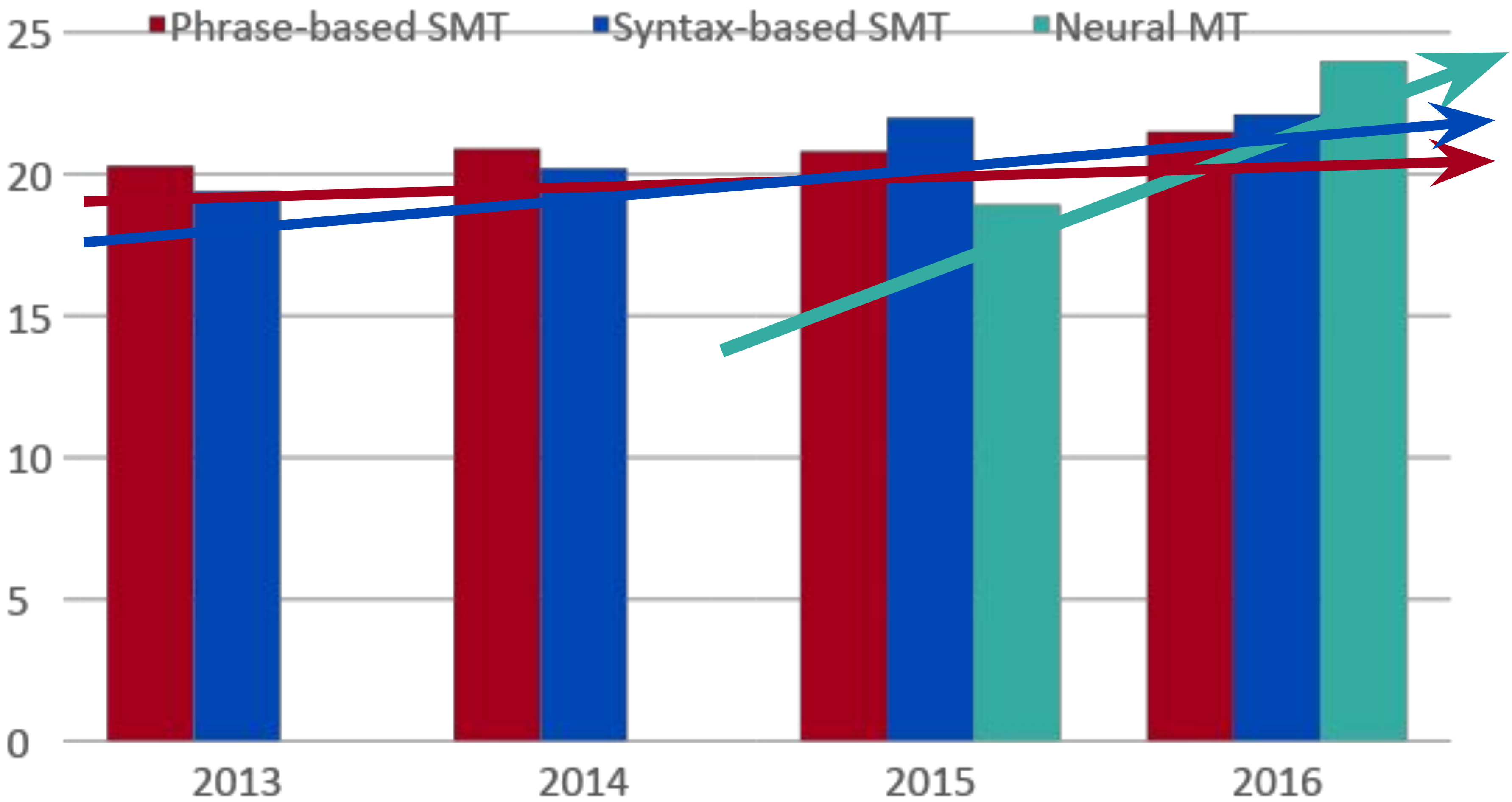
- BLEU is useful but imperfect
  - There are many valid ways to translate a sentence
  - So a good translation can get a poor BLEU score because it has low *n*-gram overlap with the human translation ☹️

Beyond BLEU

- Its own area of research
- Thought: metric without reference texts

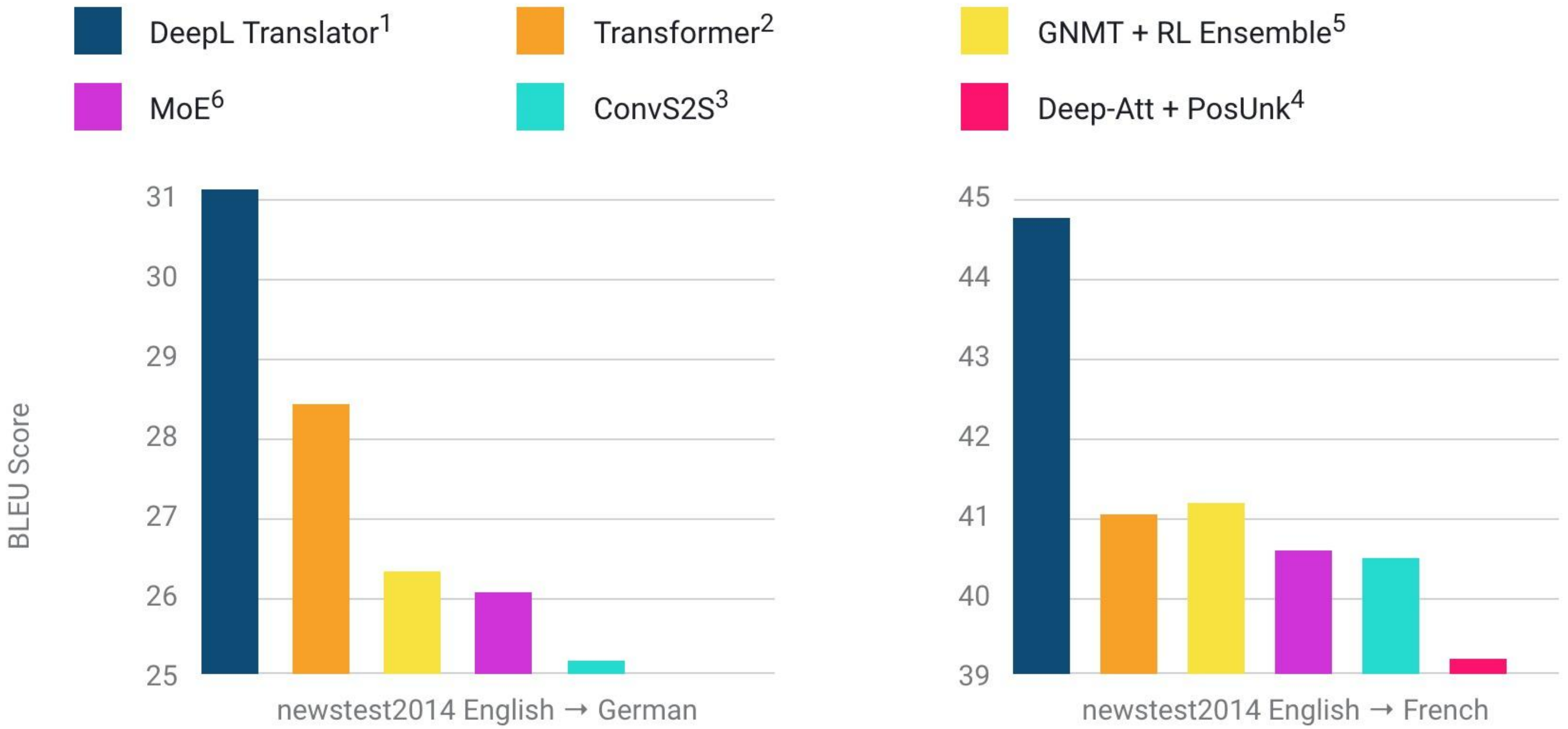
MT progress over time

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



Source: http://www.meta-net.eu/events/meta-forum-2016/slides/09_sennrich.pdf

Data data data



Source: DeepL's press release (Aug 2017)

NMT: the biggest success story of 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

So is Machine Translation solved?

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

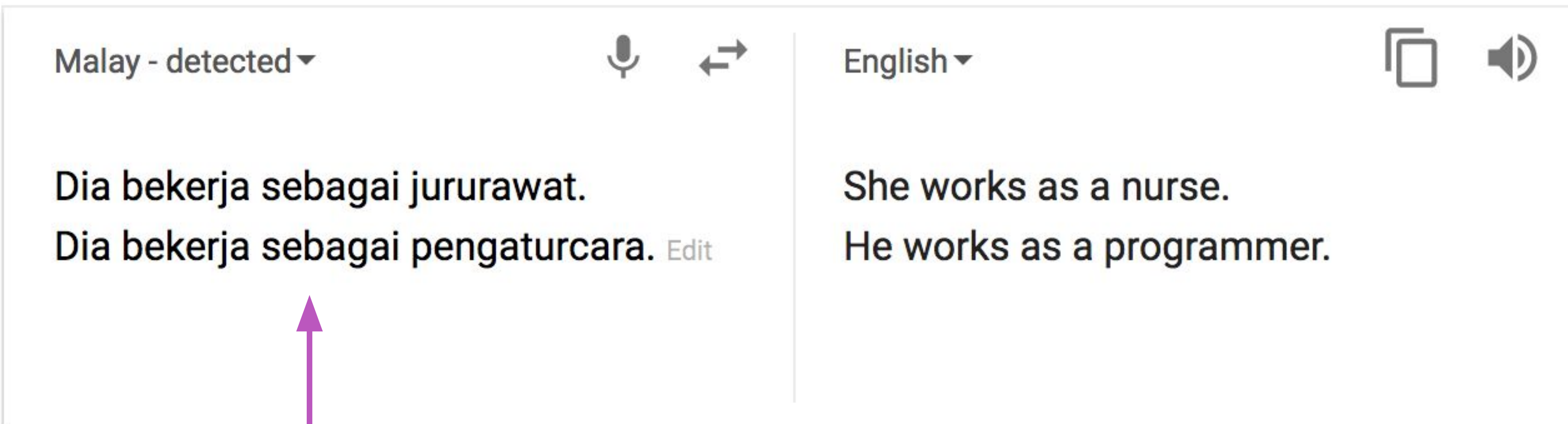
So is Machine Translation solved?

- **Nope!**
- Using common sense is still hard

?

So is Machine Translation solved?

- **Nope!**
- NMT picks up biases in training data

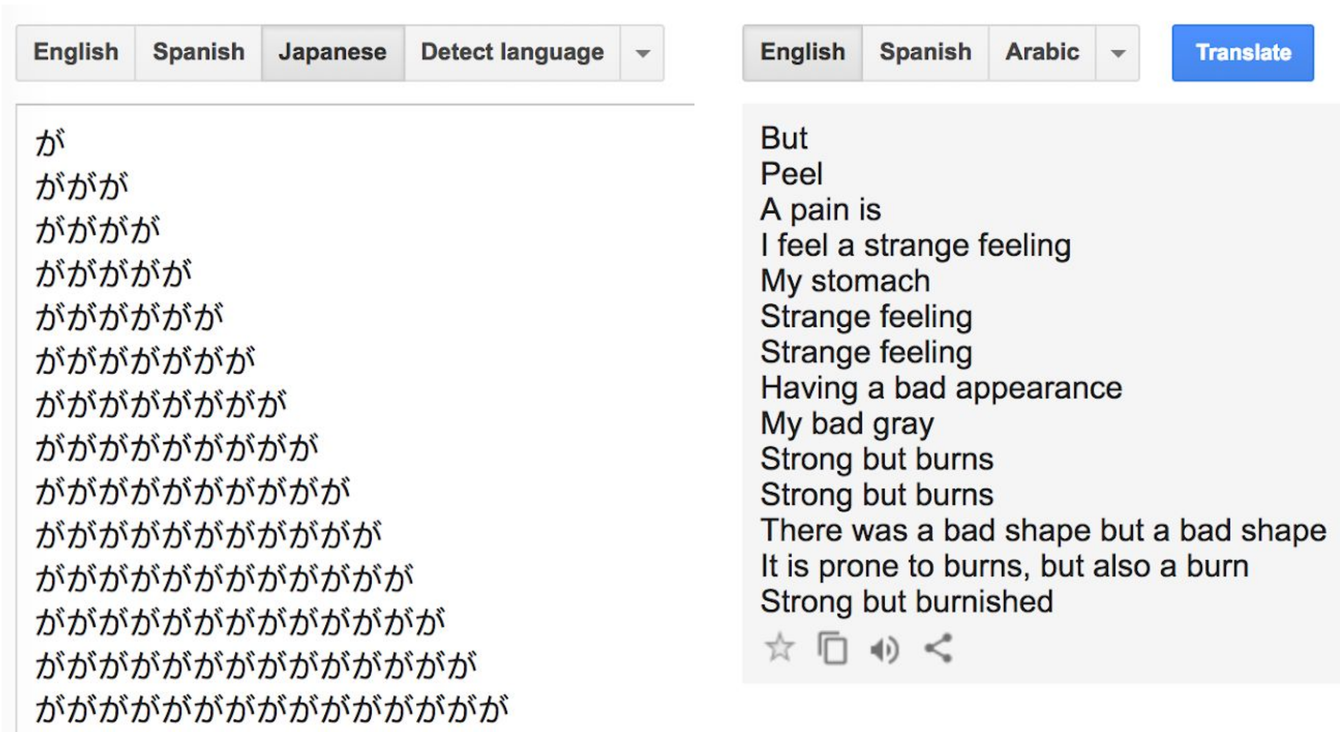


Didn't specify gender

Source: https://hackernoon.com/bias-sexist-or-this-is-the-way-it-should-be-ce1f7c8c683c

So is Machine Translation solved?

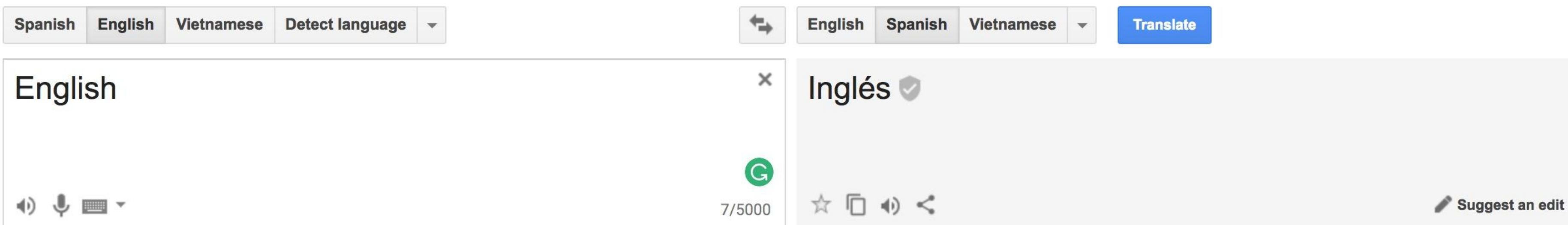
- Nope!
- Uninterpretable systems do strange things



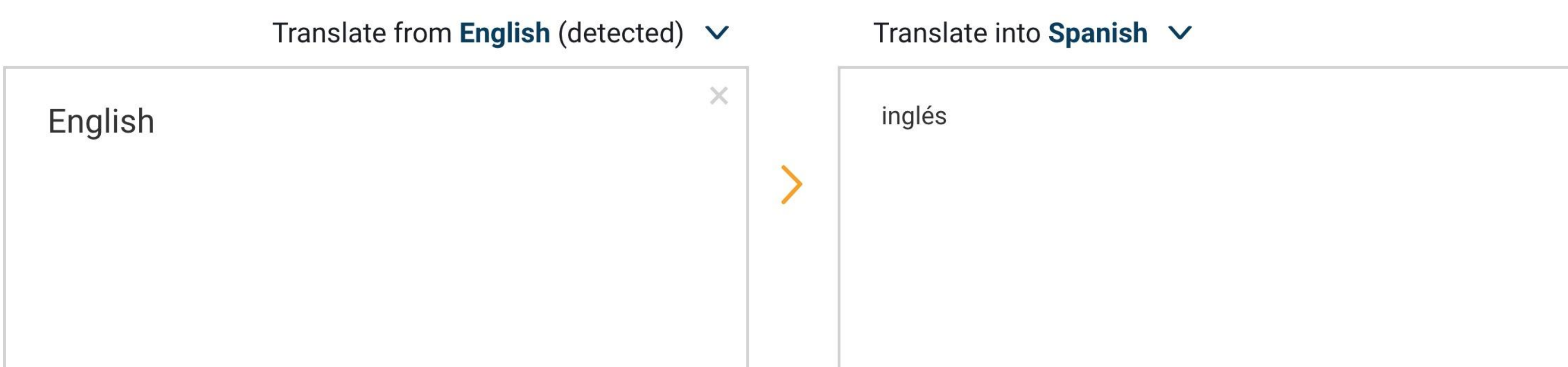
Source: http://languagelog.ldc.upenn.edu/nll/?p=35120#more-35120

Google Translate vs DeepL (2/23/2018)

Google Translate: 0



DeepL: 0



Google Translate vs DeepL (2/23/2018)

Google Translate: 0

So what if I don't know what Armageddon means? It's not the end of the world.

77/5000

Entonces, ¿qué pasa si no sé lo que significa Armageddon? No es el fin del mundo.

Suggest an edit

DeepL: 0

So what if I don't know what Armageddon means? It's not the end of the world.

¿Y qué si no sé lo que significa el Armagedón? No es el fin del mundo.

Google Translate vs DeepL (2/23/2018)

Google Translate: 0

What's the difference between in-laws and outlaws?
Outlaws are wanted.

70/5000

¿Cuál es la diferencia entre parientes políticos y fuera de la ley?
Se quieren forajidos.

Suggest an edit

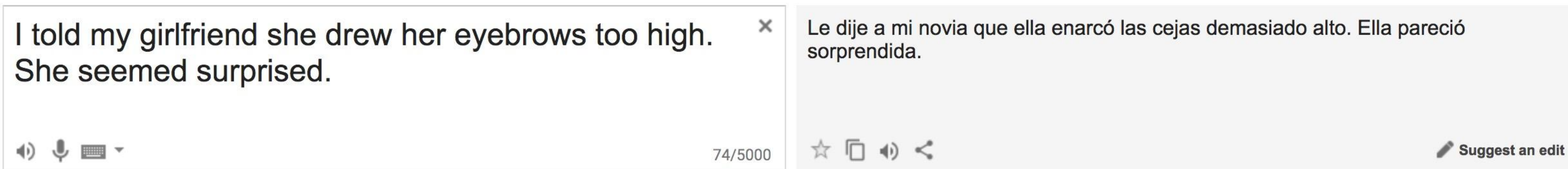
DeepL: 0

What's the difference between in-laws and outlaws?
Outlaws are wanted.

¿Cuál es la diferencia entre suegros y forajidos?
Se buscan forajidos.

Google Translate vs DeepL (2/23/2018)

Google Translate: 0



DeepL: 0

Google Translate vs DeepL (2/23/2018)

Google Translate: 0

Communism jokes aren't funny unless everyone gets them.

55/5000

Las bromas del comunismo no son divertidas a menos que todos las reciban.

Suggest an edit

DeepL: 0

Communism jokes aren't funny unless everyone gets them.

Las bromas del comunismo no son graciosas a menos que todos las entiendan.

Google Translate vs DeepL (2/23/2018)

Google Translate: 0

Sorry losers and haters, but my I.Q. is one of the highest -and you all know it! Please don't feel so stupid or insecure,it's not your fault

140/5000

Lo siento perdedores y enemigos, pero mi I.Q. es uno de los más altos, ¡y todos lo saben! Por favor, no te sientas tan estúpido o inseguro, no es tu culpa

Suggest an edit

DeepL: 0

Sorry losers and haters, but my I.Q. is one of the highest -and you all know it! Please don't feel so stupid or insecure,it's not your fault

Lo siento perdedores y odiosos, pero mi coeficiente intelectual. es uno de los más altos - y todos ustedes lo saben! Por favor no te sientas tan estúpido o inseguro, no es tu culpa.

NMT research continues

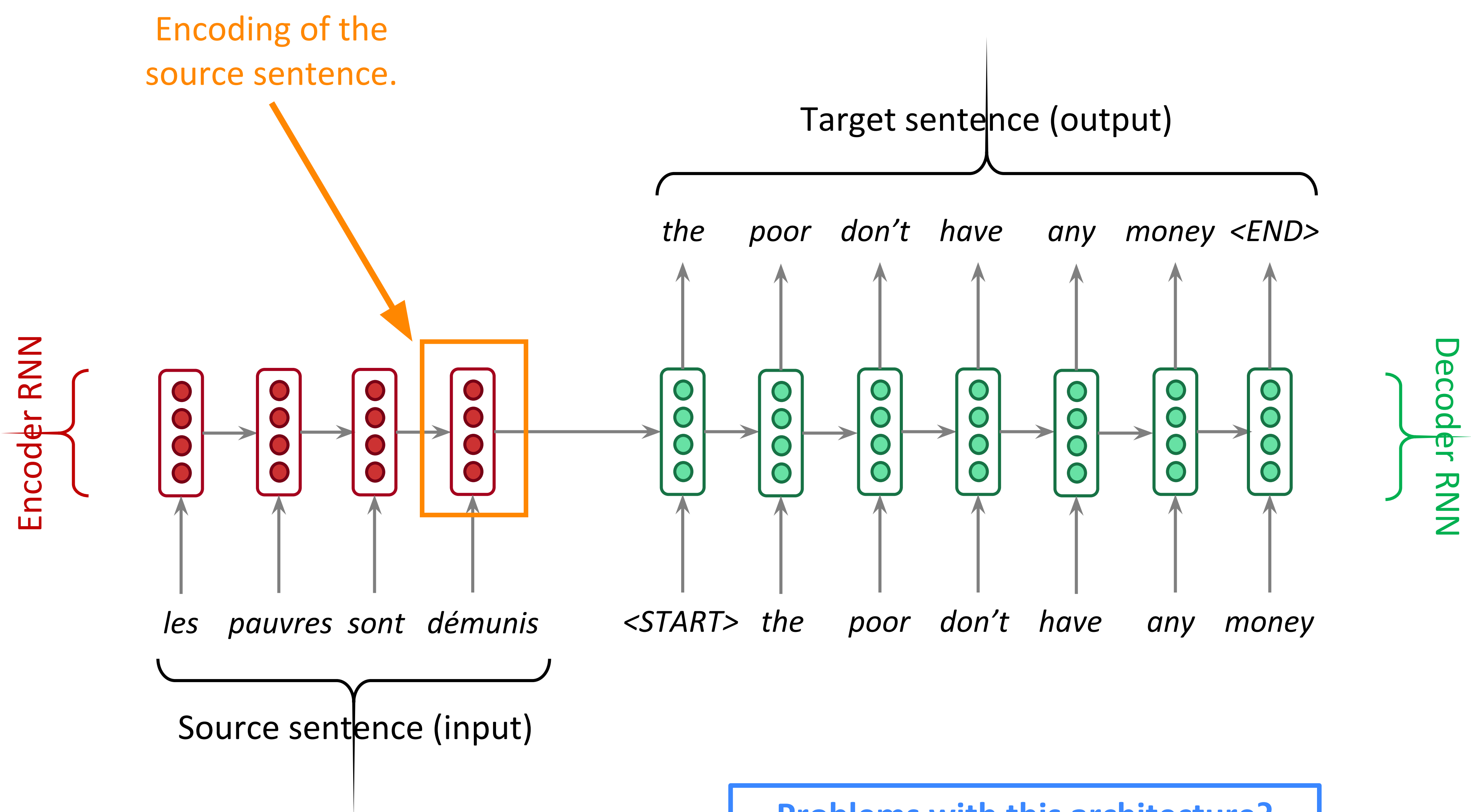
NMT is the **flagship task** for NLP Deep Learning

- NMT research has pioneered many of the recent innovations of NLP Deep Learning

- In **2018**: NMT research continues to thrive
  - Researchers have found *many, many* improvements to the "vanilla" seq2seq NMT system we've presented today
  - But one improvement is so integral that it is the new vanilla…

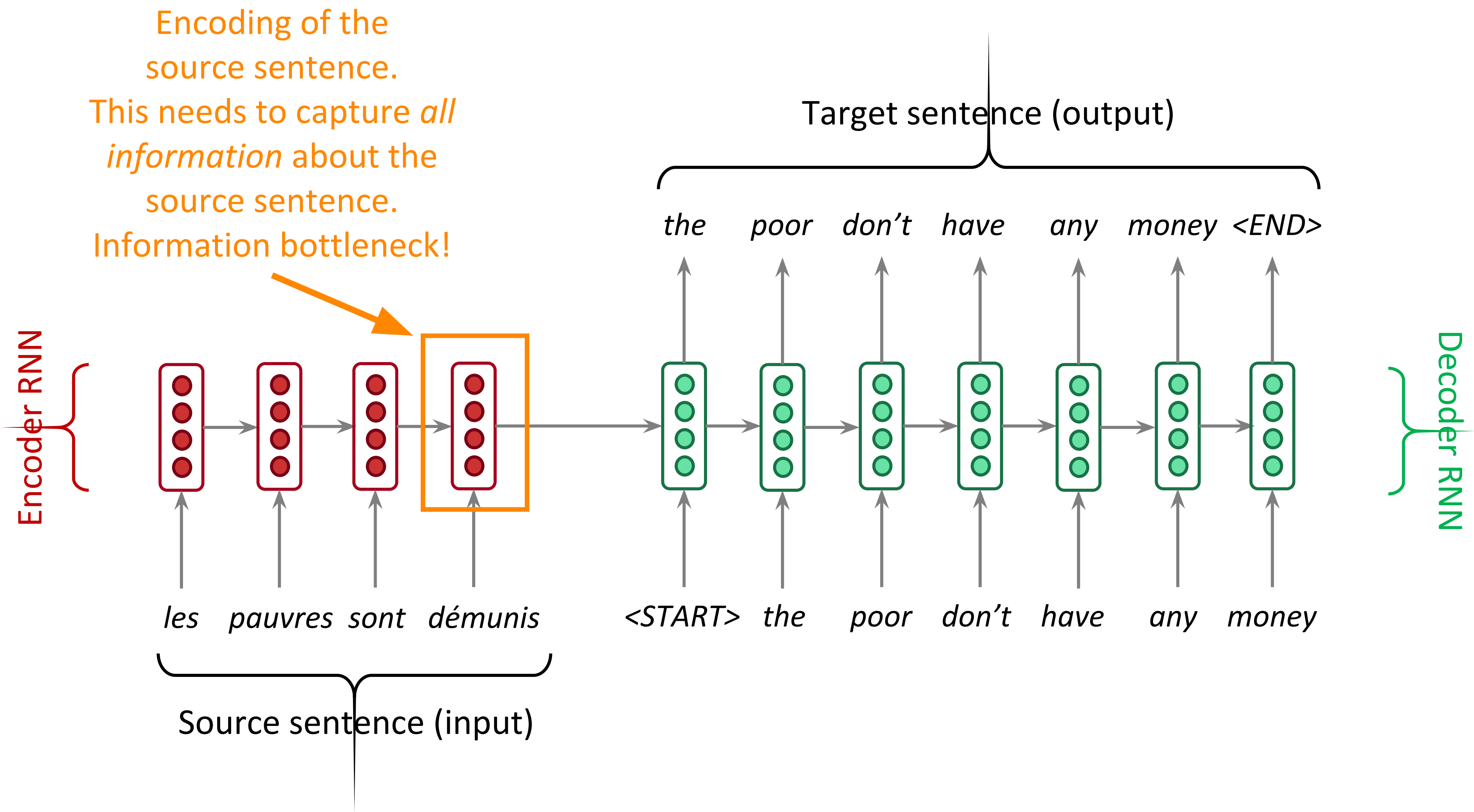
ATTENTION

Sequence-to-sequence: the bottleneck problem



Problems with this architecture?

Sequence-to-sequence: the bottleneck problem

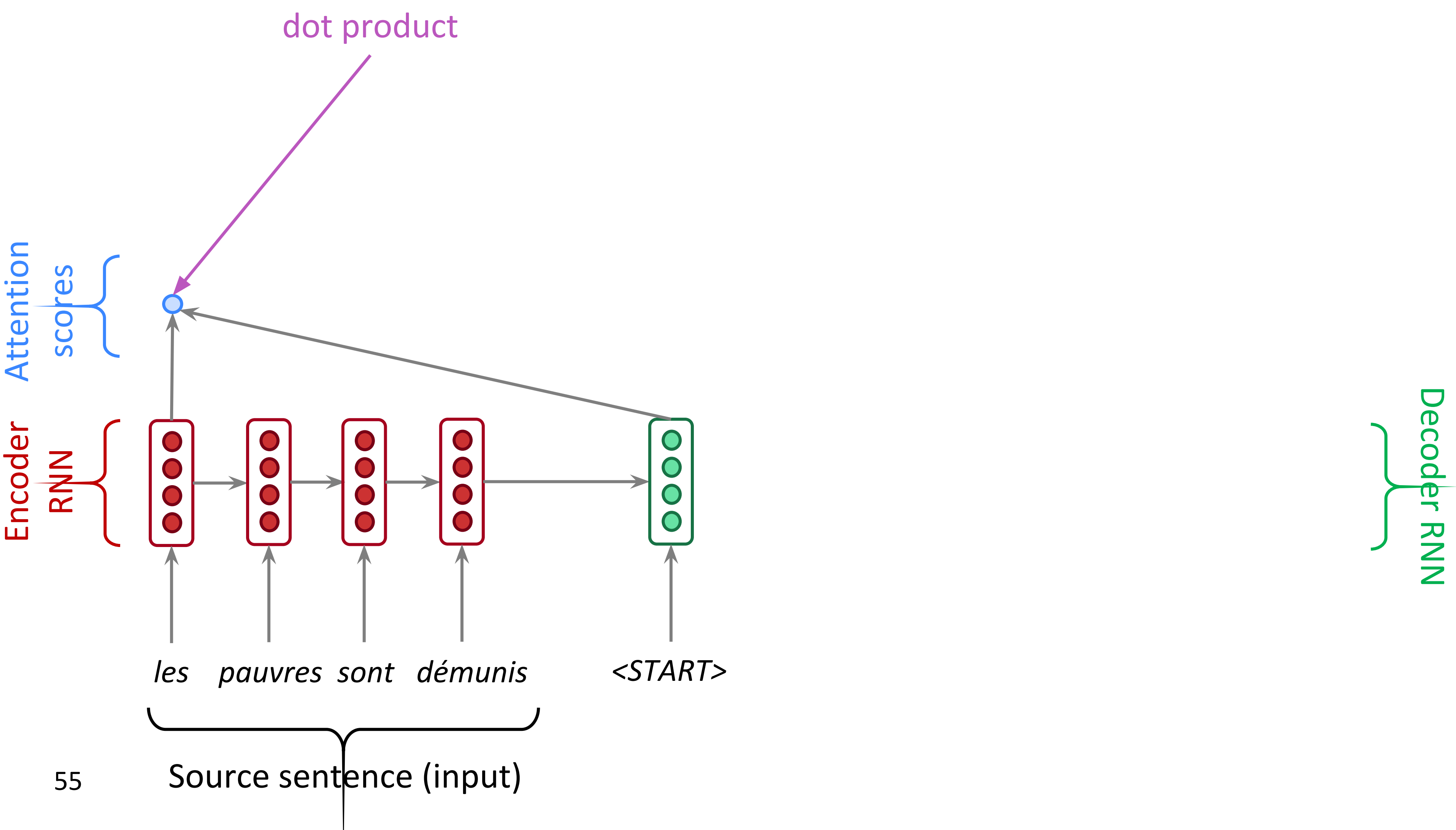


Attention

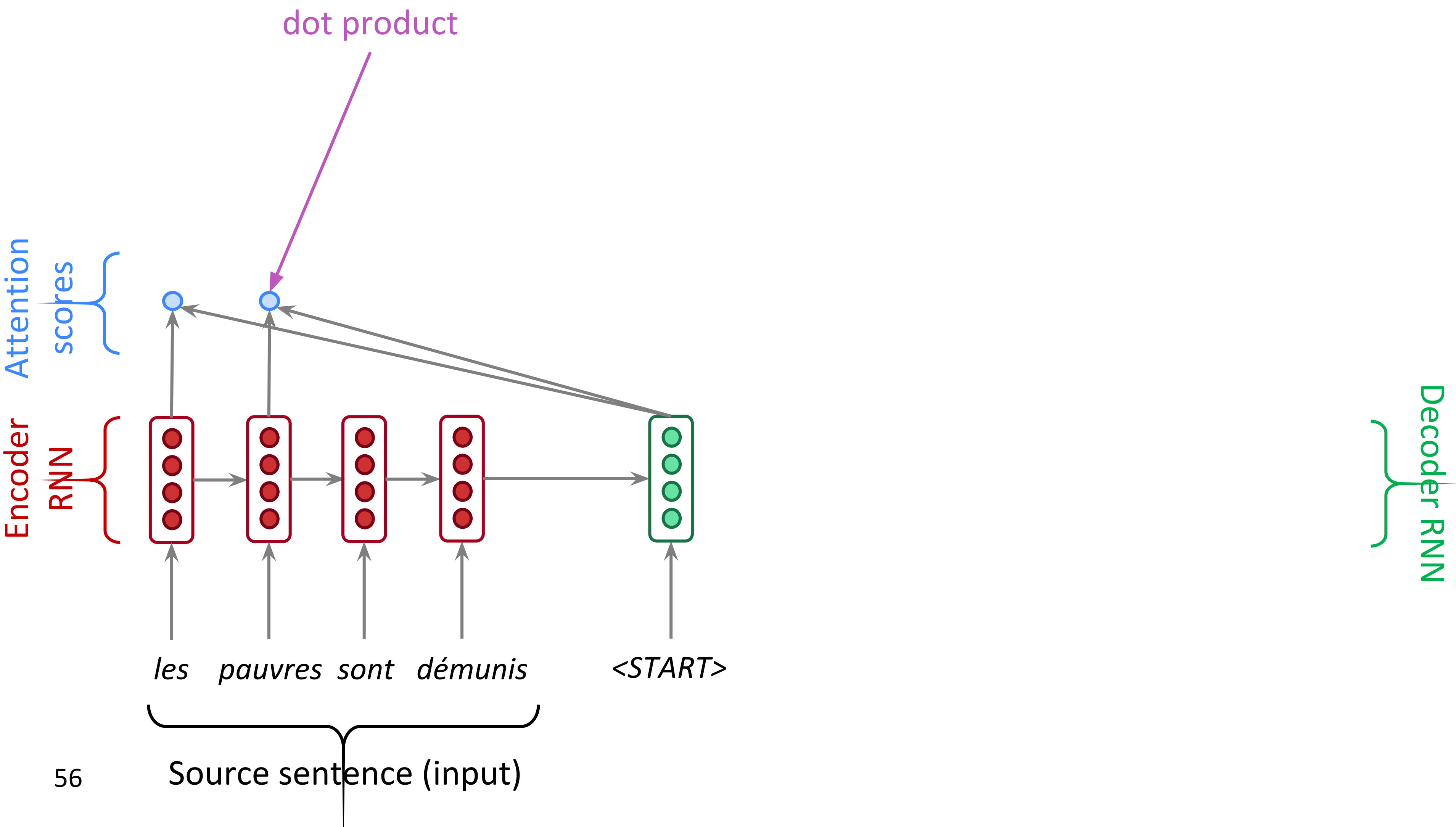
- **Attention** provides a solution to the bottleneck problem.

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

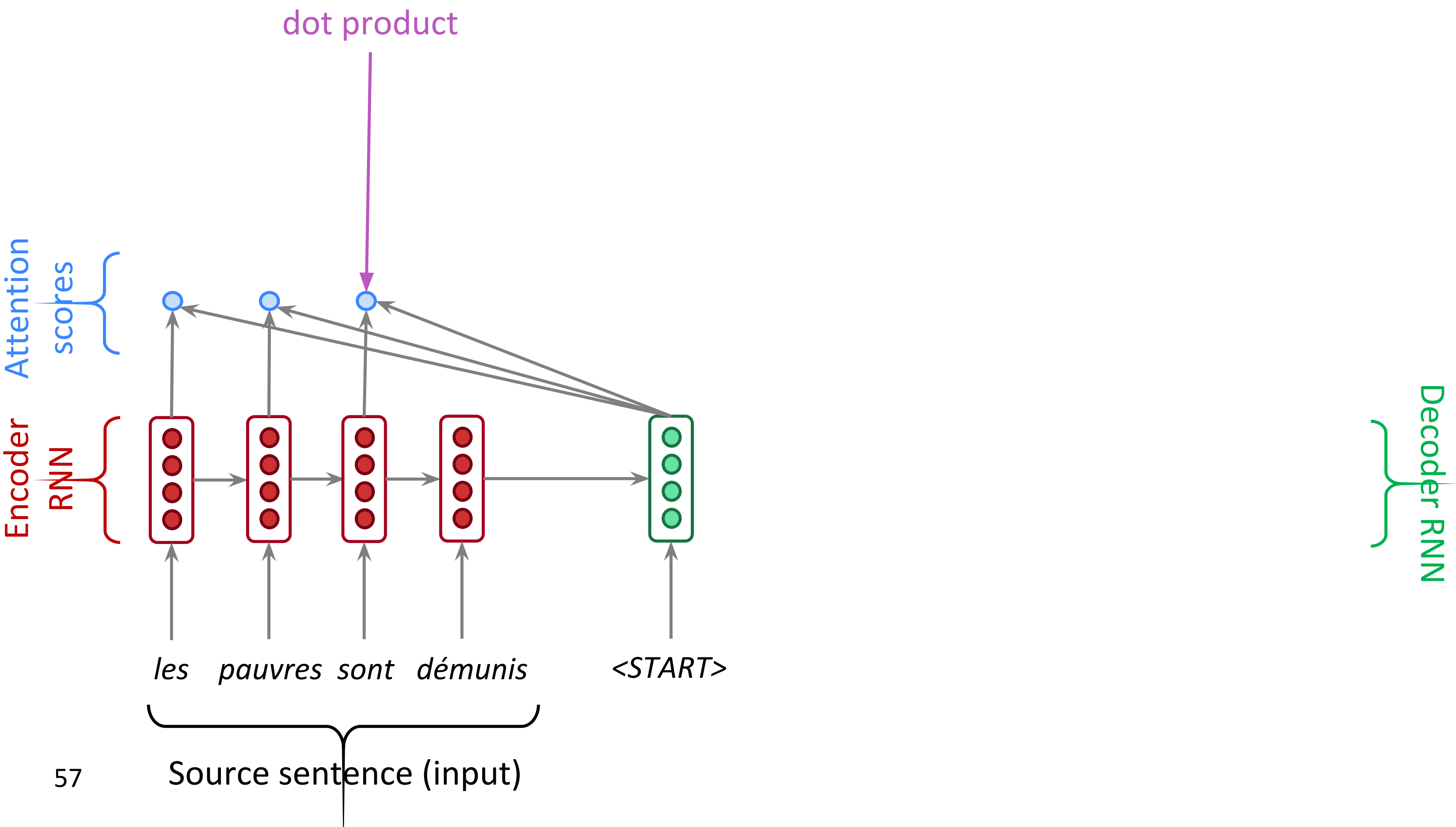
Sequence-to-sequence with attention



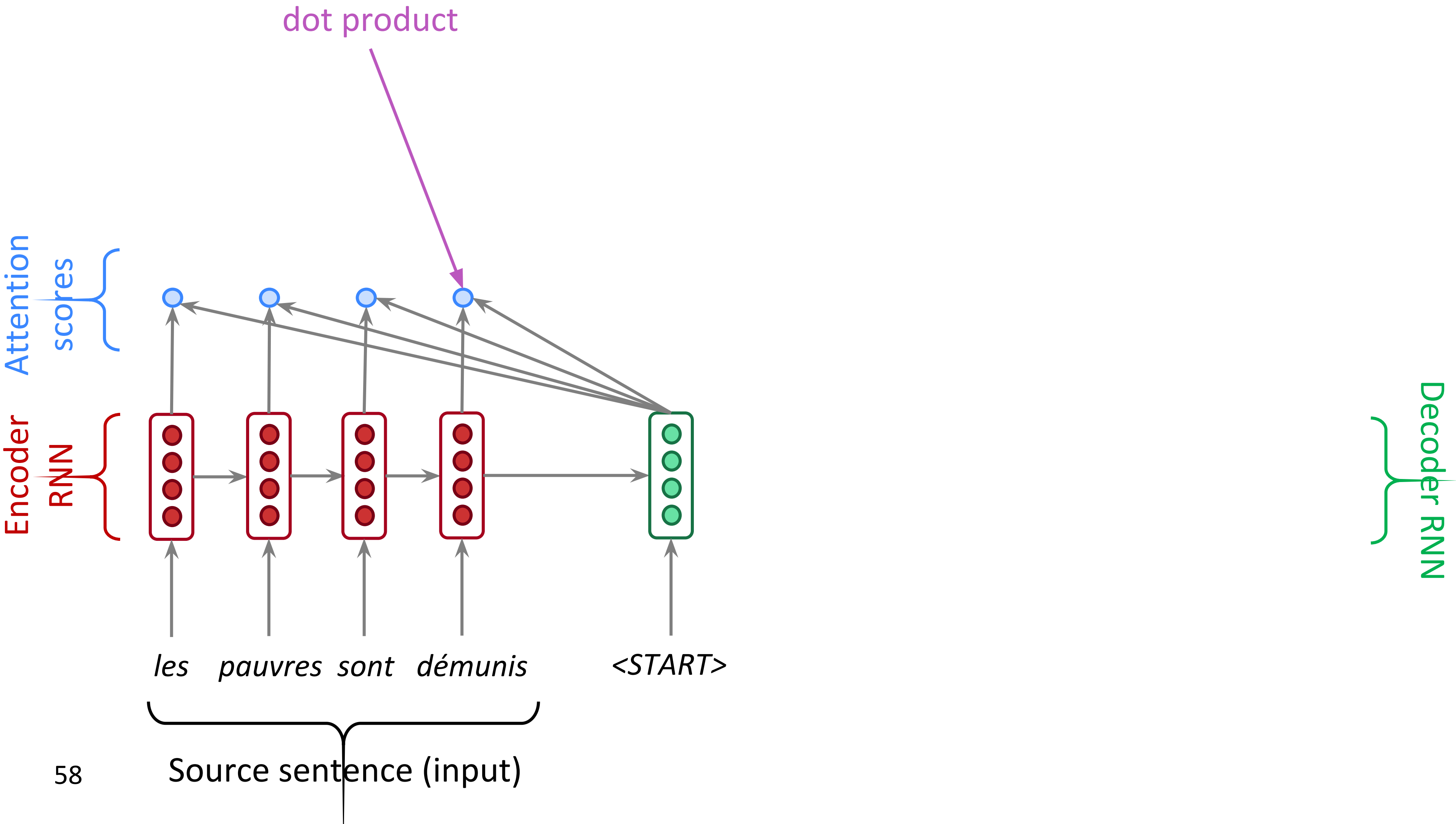
Sequence-to-sequence with attention



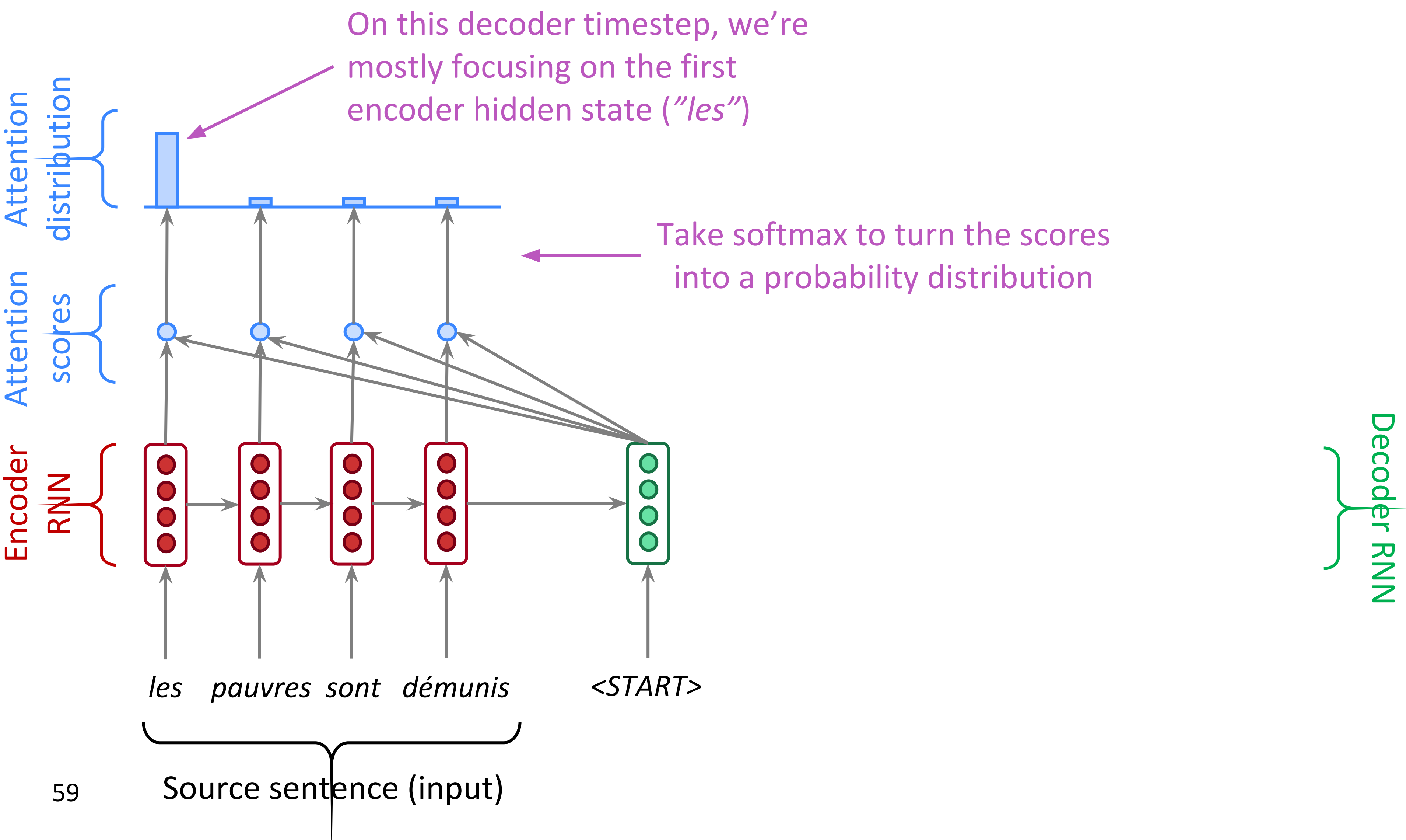
Sequence-to-sequence with attention



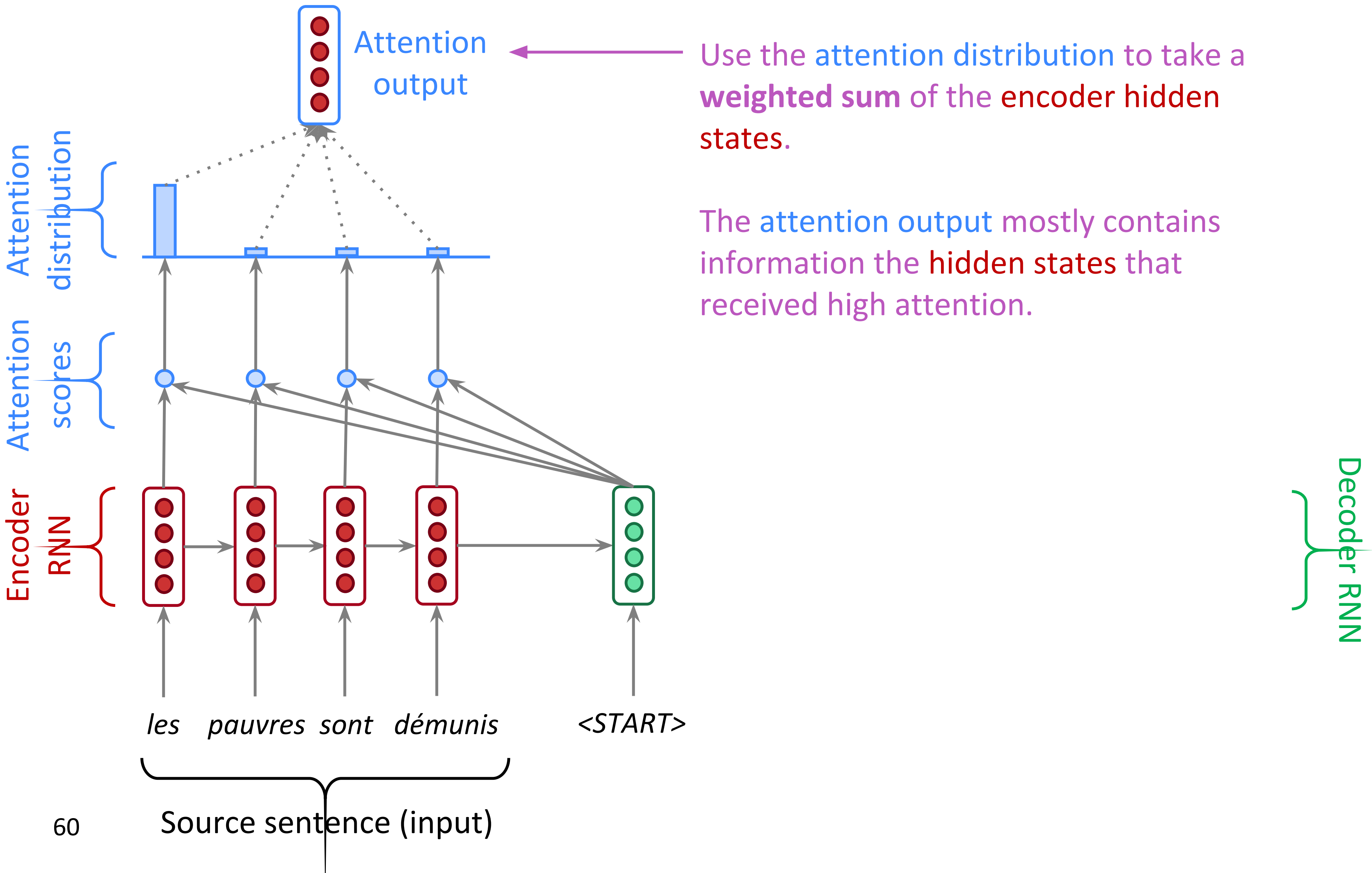
Sequence-to-sequence with attention



Sequence-to-sequence with attention



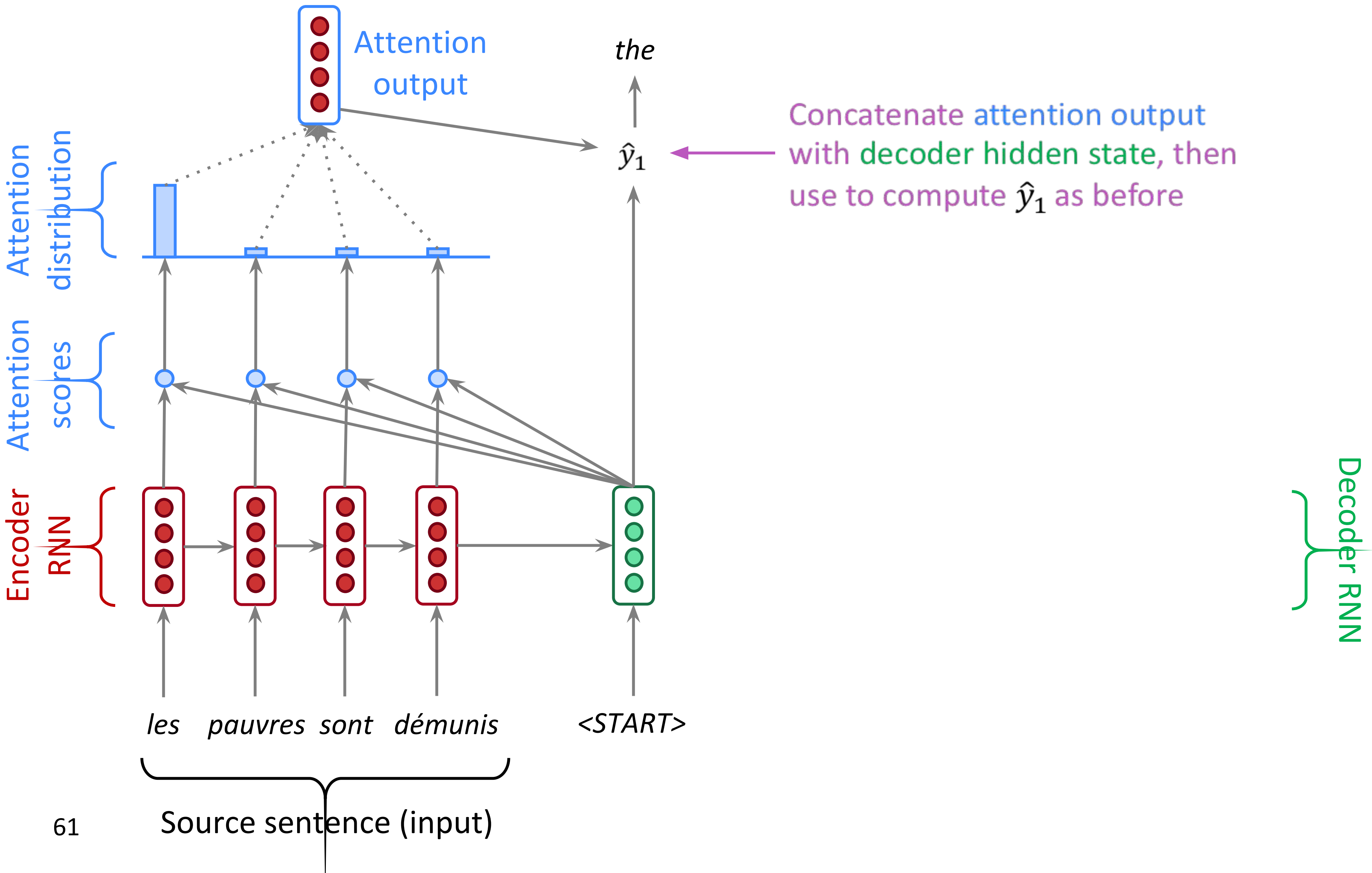
Sequence-to-sequence with attention



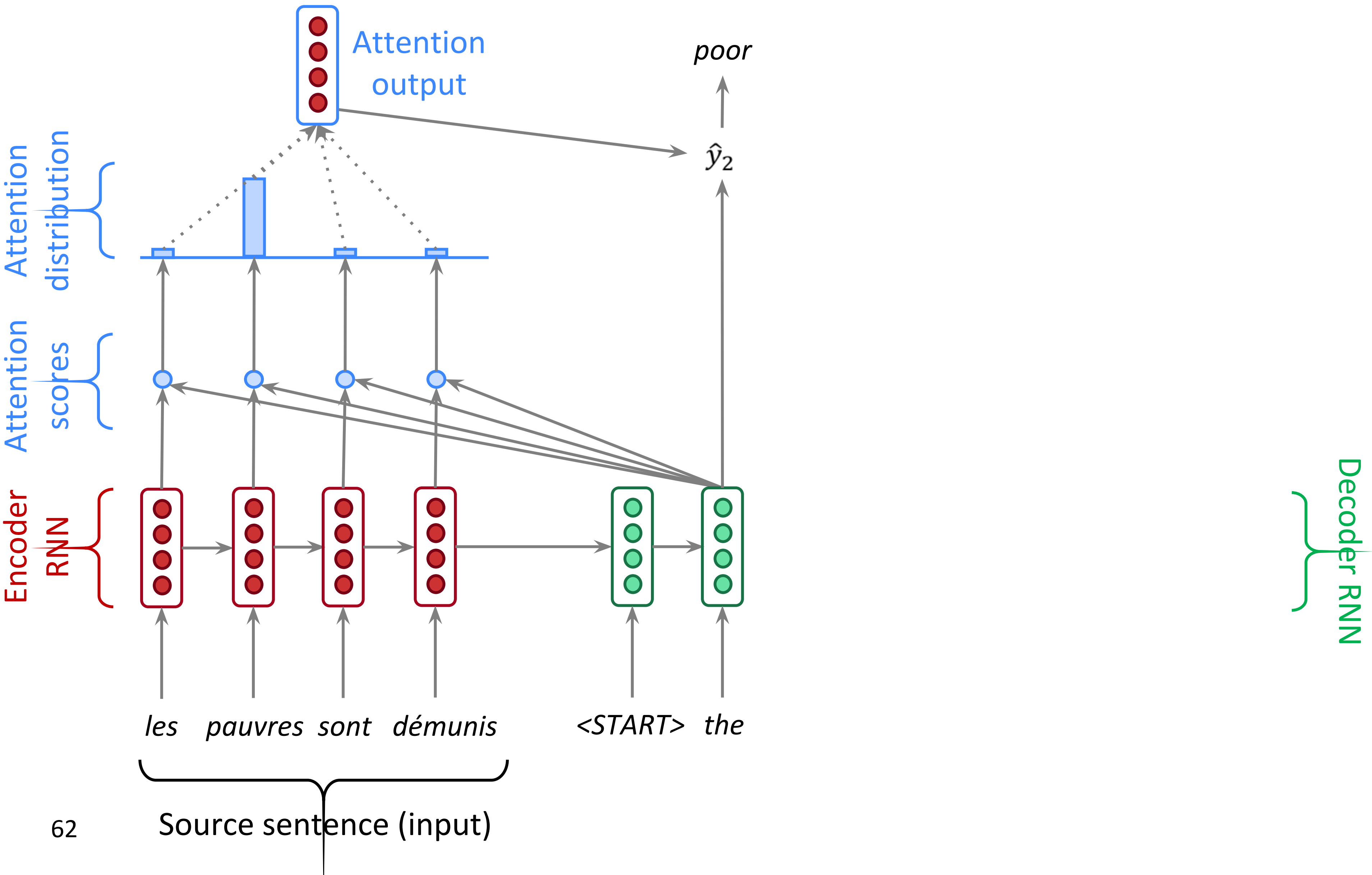
Use the attention distribution to take a **weighted sum** of the encoder hidden states.

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

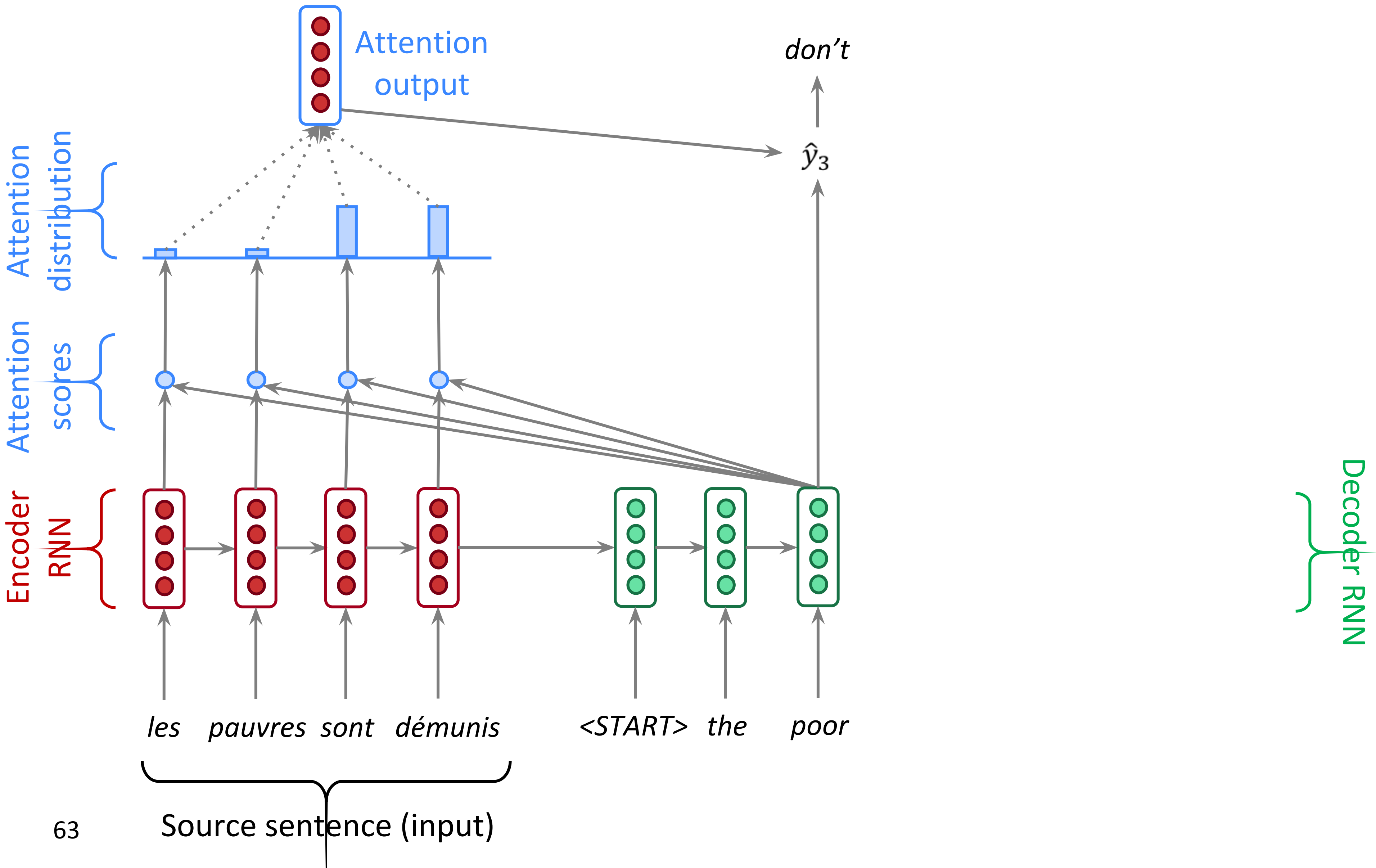
Sequence-to-sequence with attention



Sequence-to-sequence with attention



Sequence-to-sequence with attention



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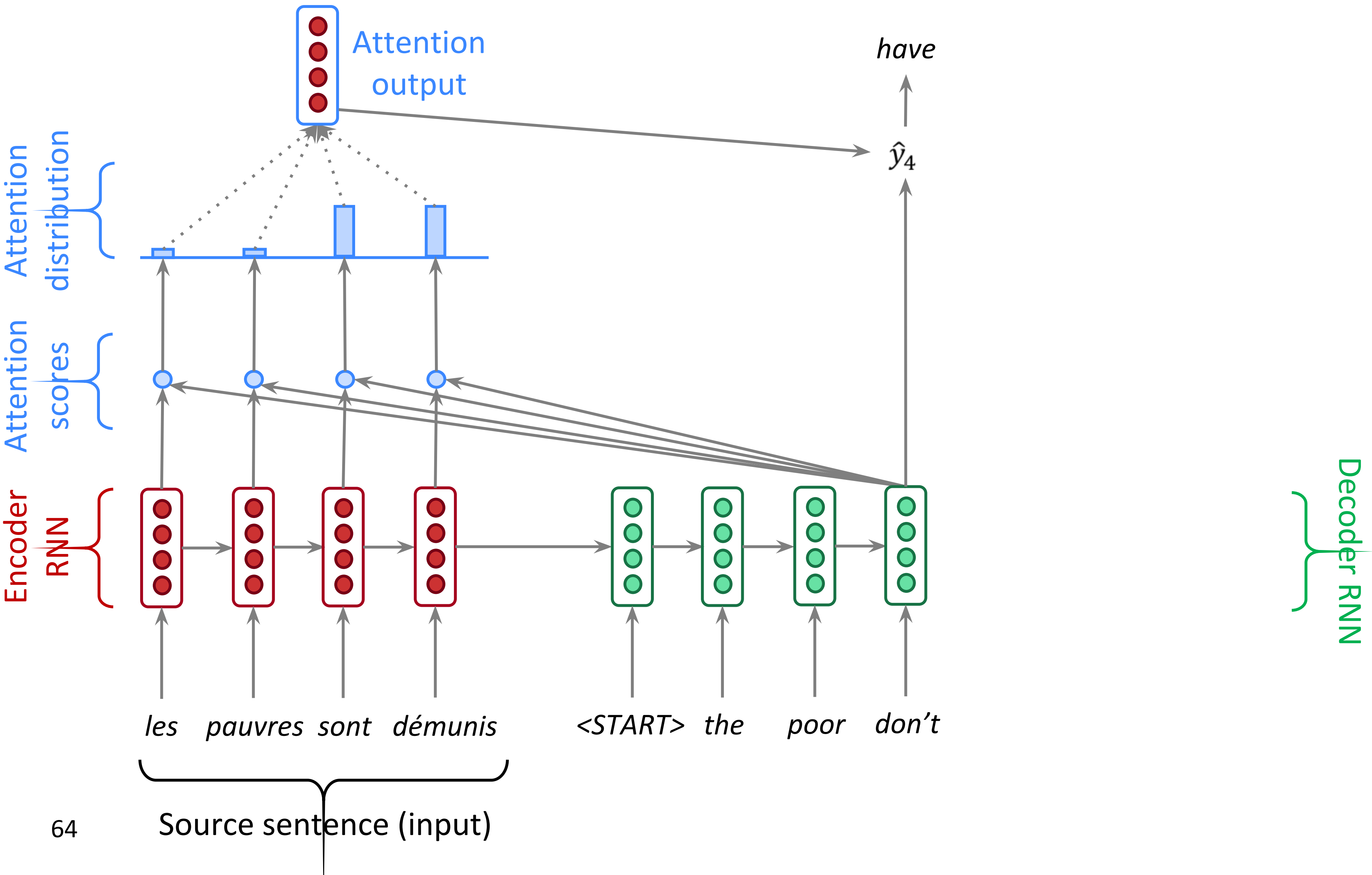

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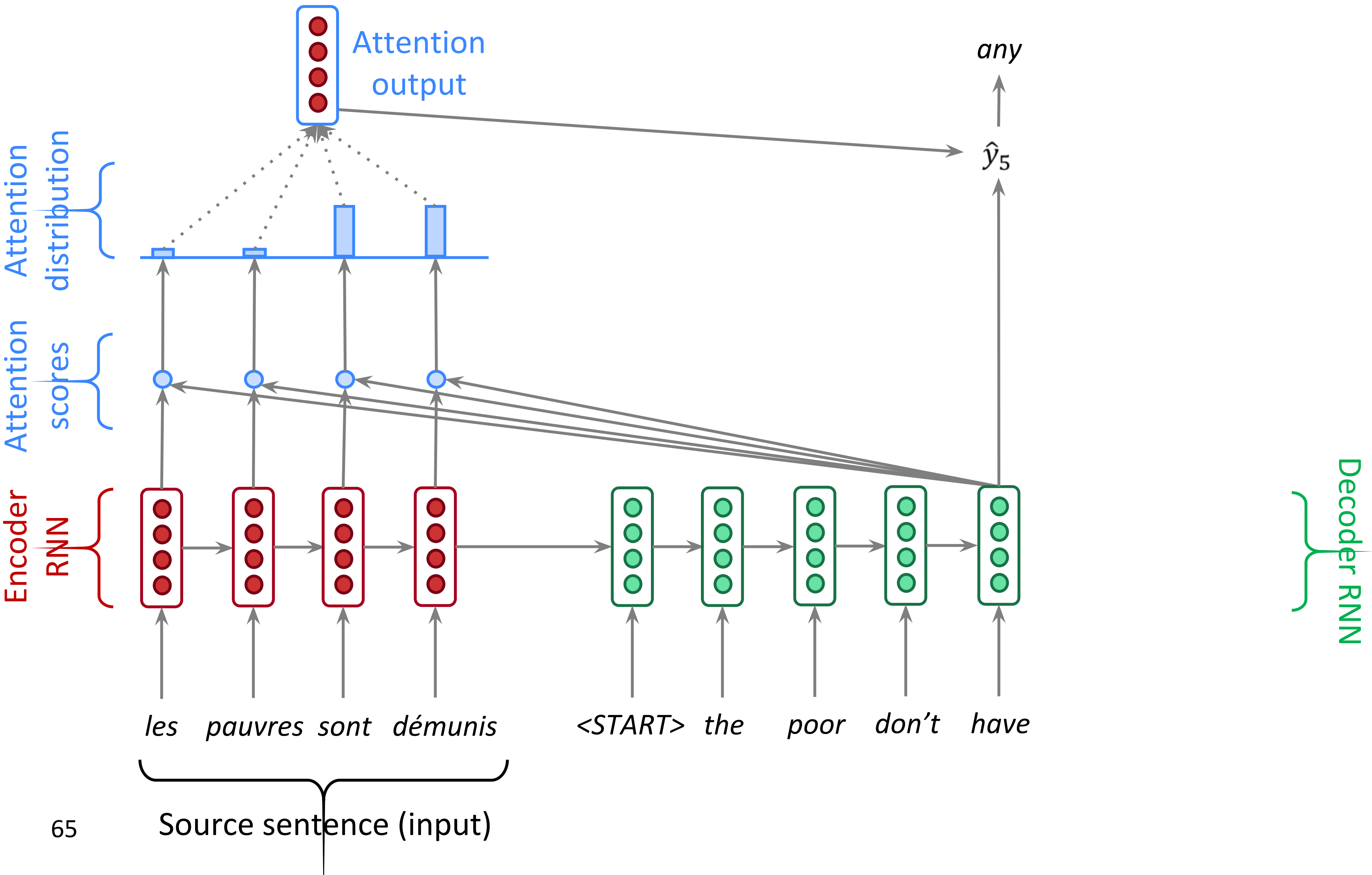
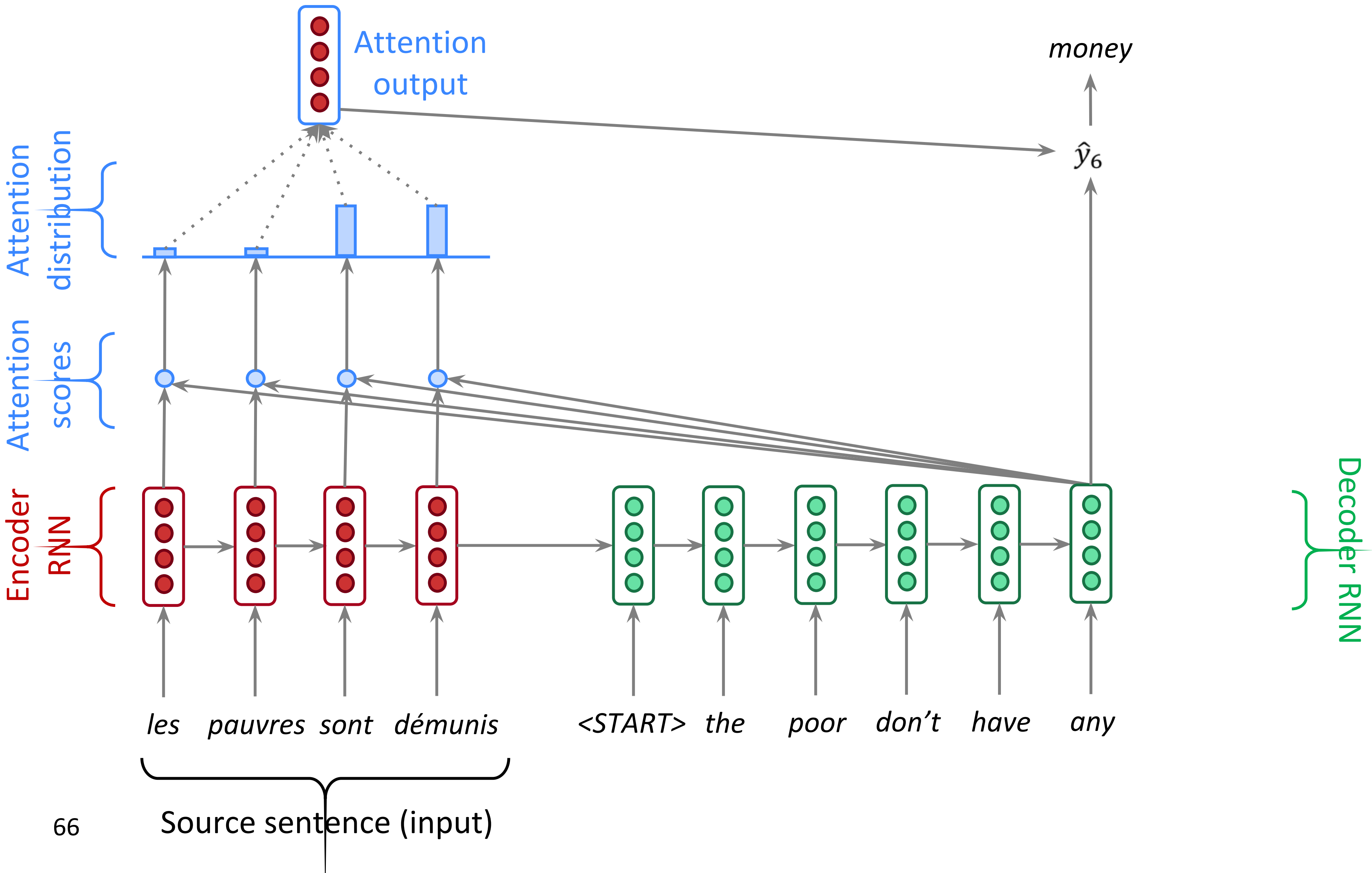


Sequence-to-sequence with attention



Attention: in equations

- 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 $\boldsymbol{a}_t$

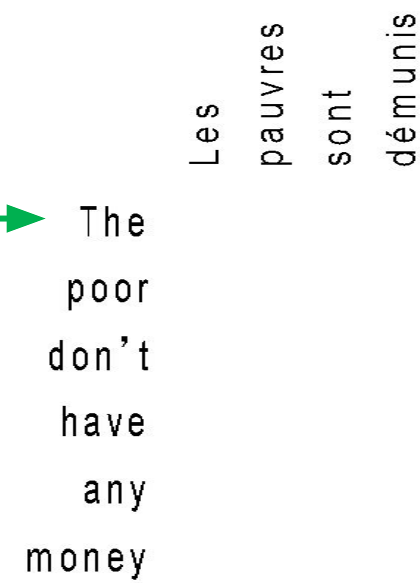
$$\boldsymbol{a}_t = \sum_{i=1}^{N} \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

- 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 is great

- 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



Recap

- We learned the history of Machine Translation (MT)

- 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!

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 $\rightarrow$ short text)
  - Dialogue (previous utterances $\rightarrow$ next utterance)
  - Parsing (input text $\rightarrow$ output parse as sequence)
  - Code generation (natural language $\rightarrow$ Python code)

Next class

- Transformers (guest lecture by Lukasz Kaiser)