Natural Language Processing with Deep Learning
CS224N/Ling284

Lecture 10:
Machine Translation,
Sequence-to-sequence and Attention

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Announcements

- Honor code issues: Assignment 2
- Assignment 3 released
- Azure credits released
- Default final project update:
  - New handout released
  - Submission instructions released
- Custom final project: you should receive feedback on your proposal this week
- Midterm grades: released after lecture

Happy Valentines Day!

RNN-generated candy hearts

Source: http://aiweirdness.com/post/170820844947/more-candy-hearts-by-neural-network

Welcome to the second half of the course!

- Remaining lectures are mostly geared towards projects
- We'll bring you to the cutting-edge of NLP+DL research
- Lectures will be more high-level
  - No more gradient computations!
  - Sometimes we'll sketch an overview – if you're interested in a topic, you can read more after class
- **However**: today's lecture will cover two **core** NLP Deep Learning techniques

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.

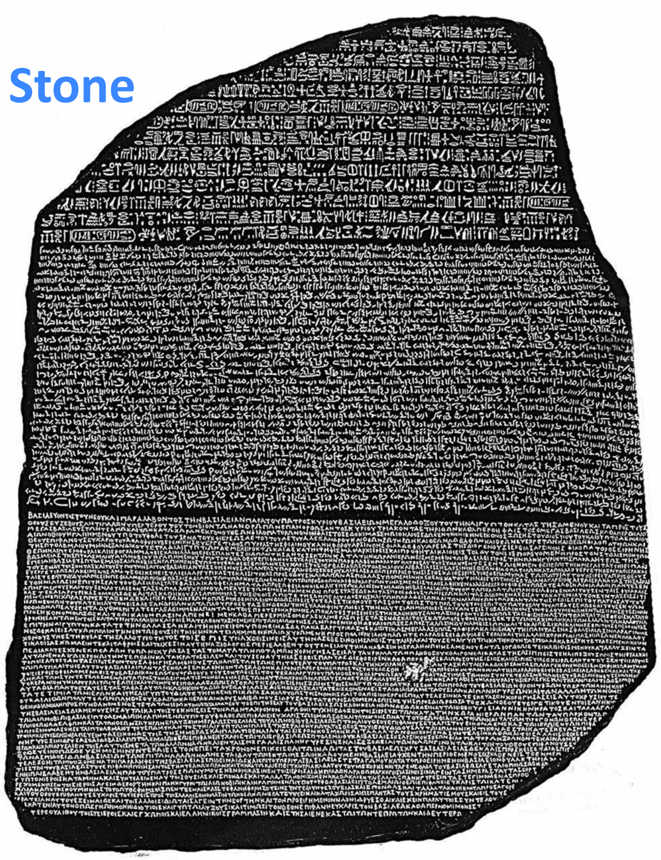
Language Model

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



Ancient Egyptian

Demotic

Ancient Greek

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

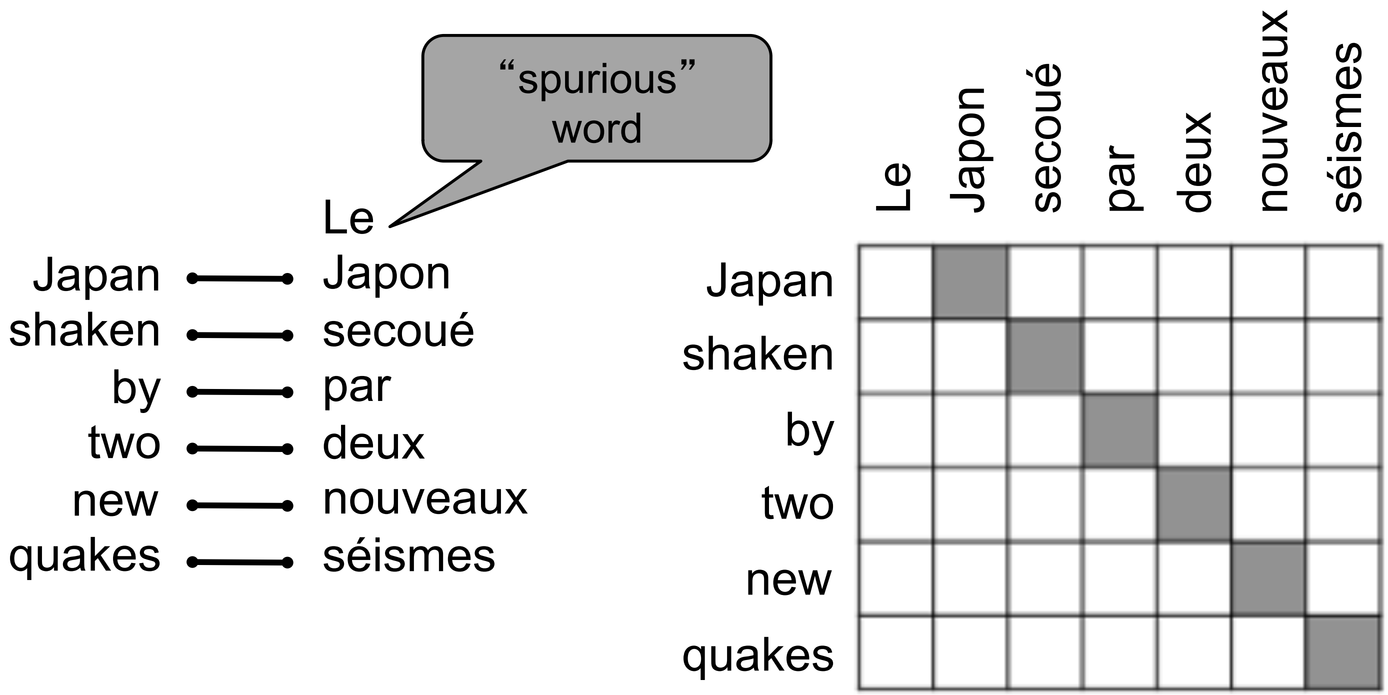
$$P(x, a|y)$$

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

What is alignment?

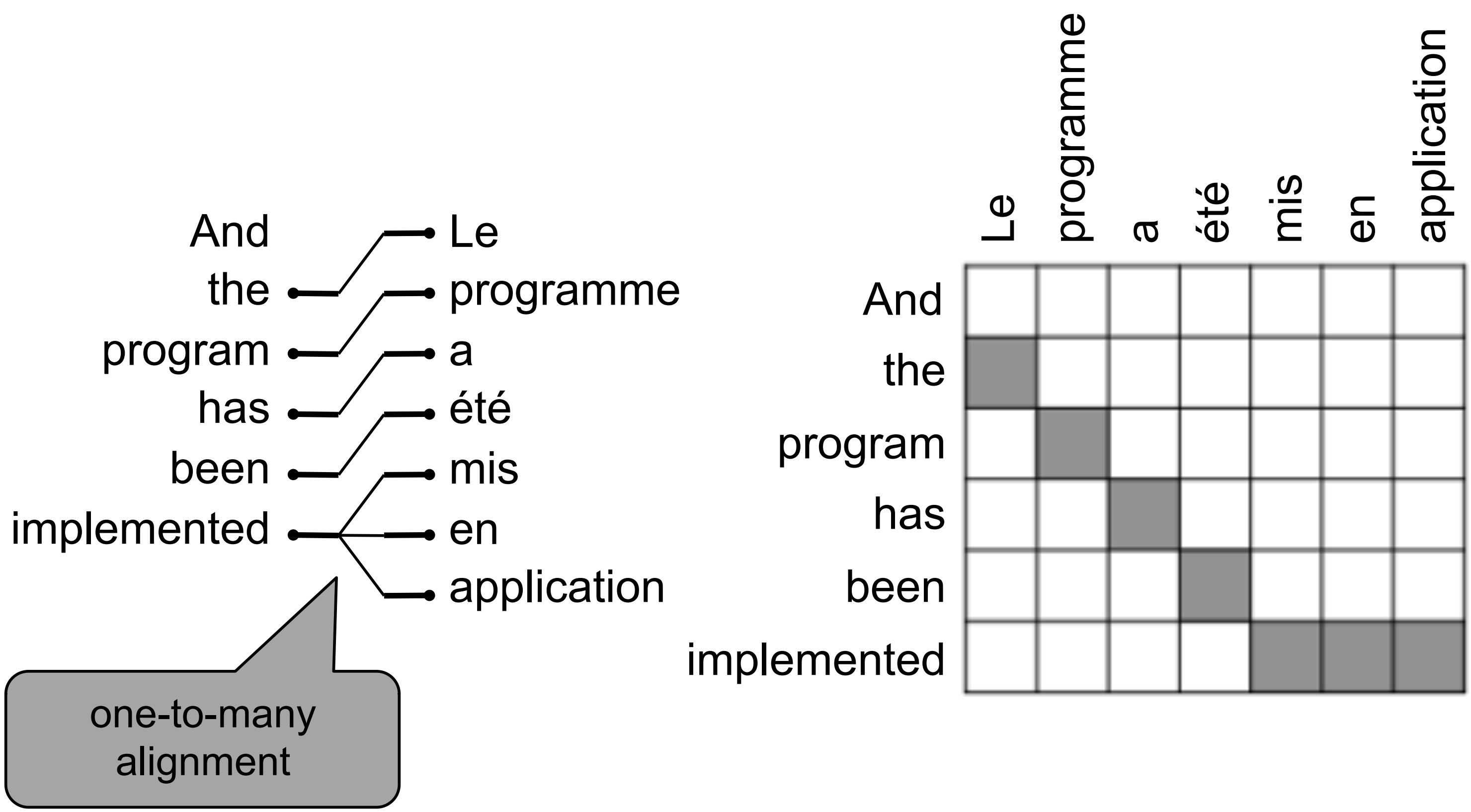
Alignment is the correspondence between particular words in the translated sentence pair.

- Note: Some words have no counterpart



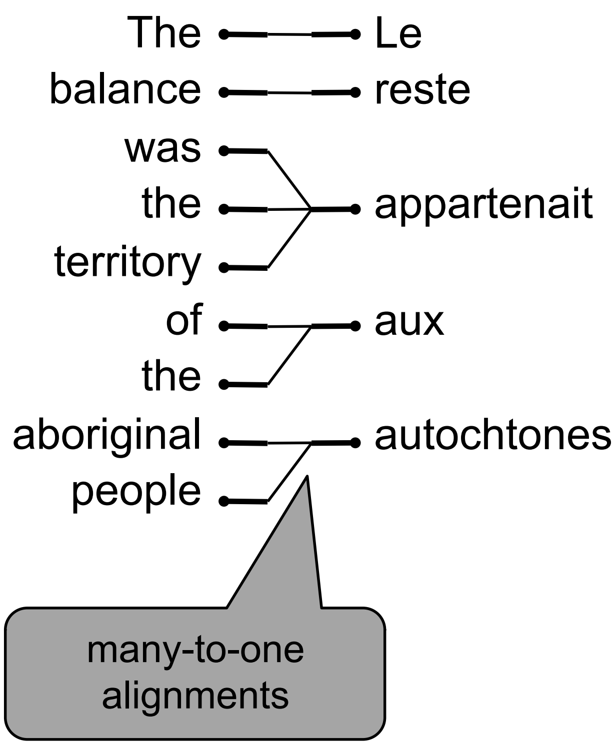
Alignment is complex

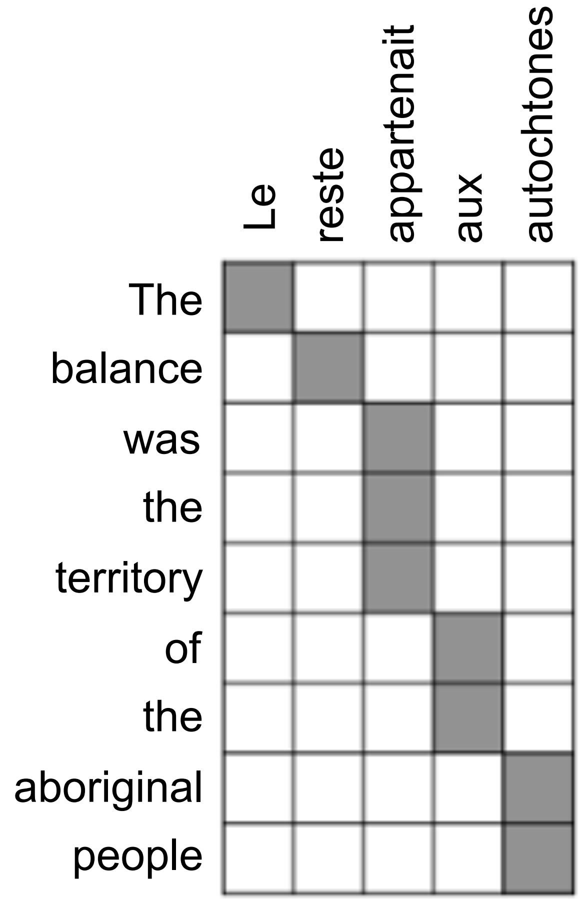
Alignment can be one-to-many (these are “fertile” words)



Alignment is complex

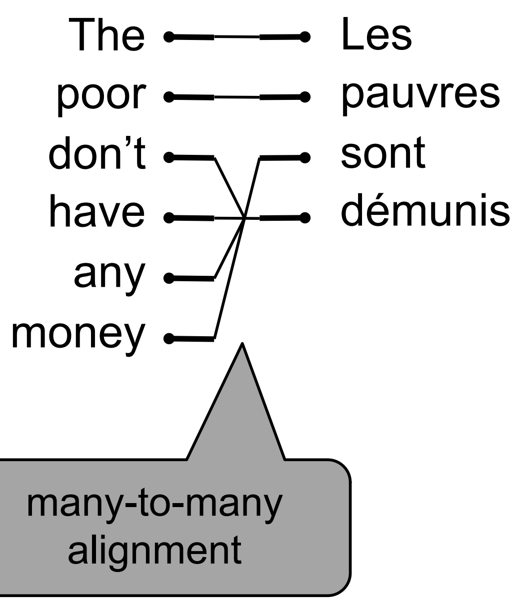
Alignment can be many-to-one

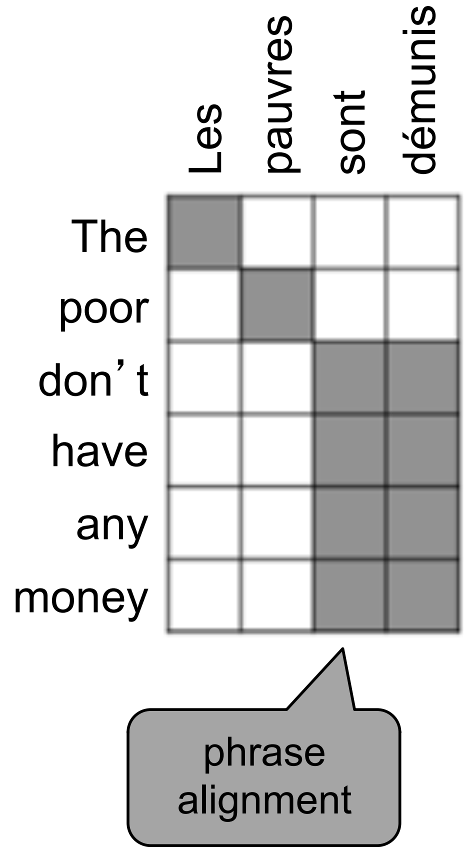




Alignment is complex

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





1990s-2010s: Statistical Machine Translation

- Question: How to learn translation model $P(x|y)$?
- First, need large amount of parallel data
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- 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*

- We learn $P(x, a|y)$ as a combination of many factors, including:
  - Probability of particular words aligning
    - Also depends on position in sentence
  - Probability of particular words having particular fertility
  - Etc.

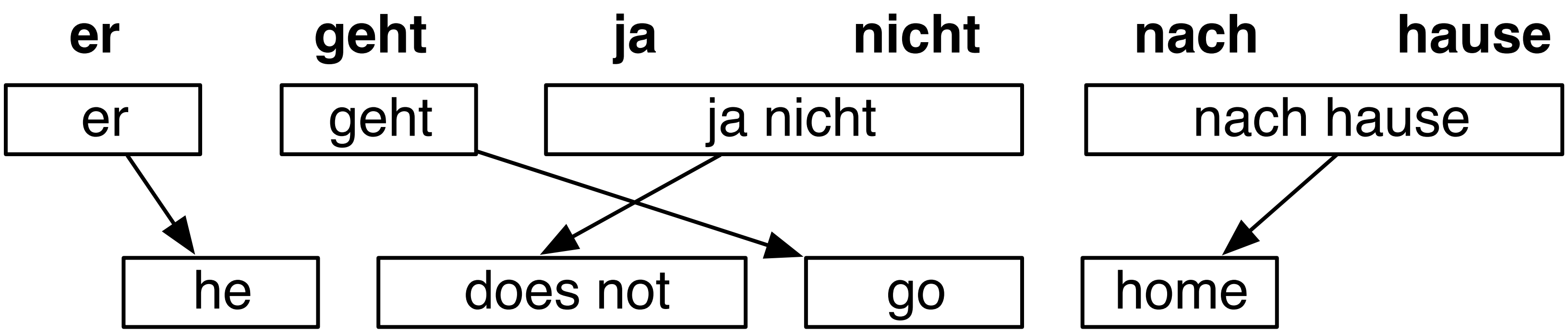
1990s-2010s: Statistical Machine Translation

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

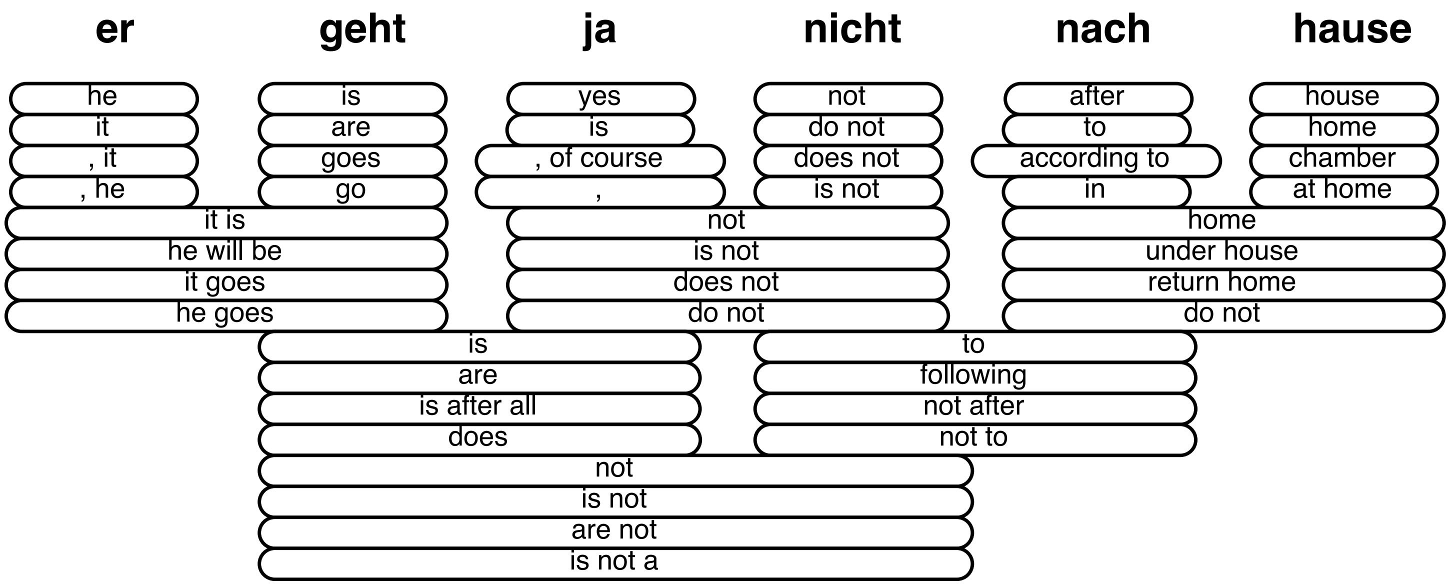
<u>Question:</u>
How to compute
this argmax?

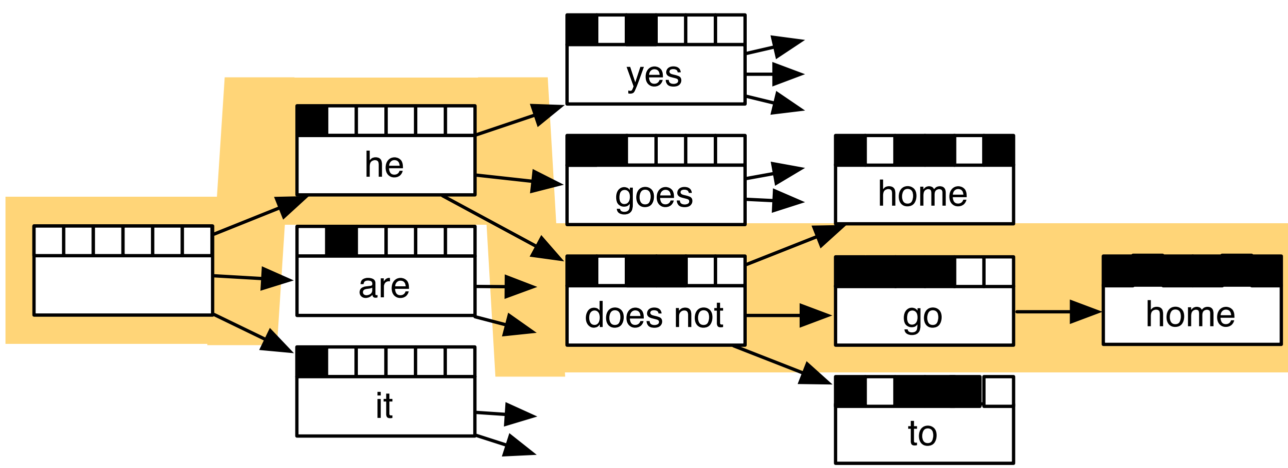
- We could enumerate every possible *y* and calculate the probability? → Too expensive!
- **<u>Answer:</u>** Use a heuristic search algorithm to gradually build up the the translation, discarding hypotheses that are too low-probability

Searching for the best translation



Searching for the best translation



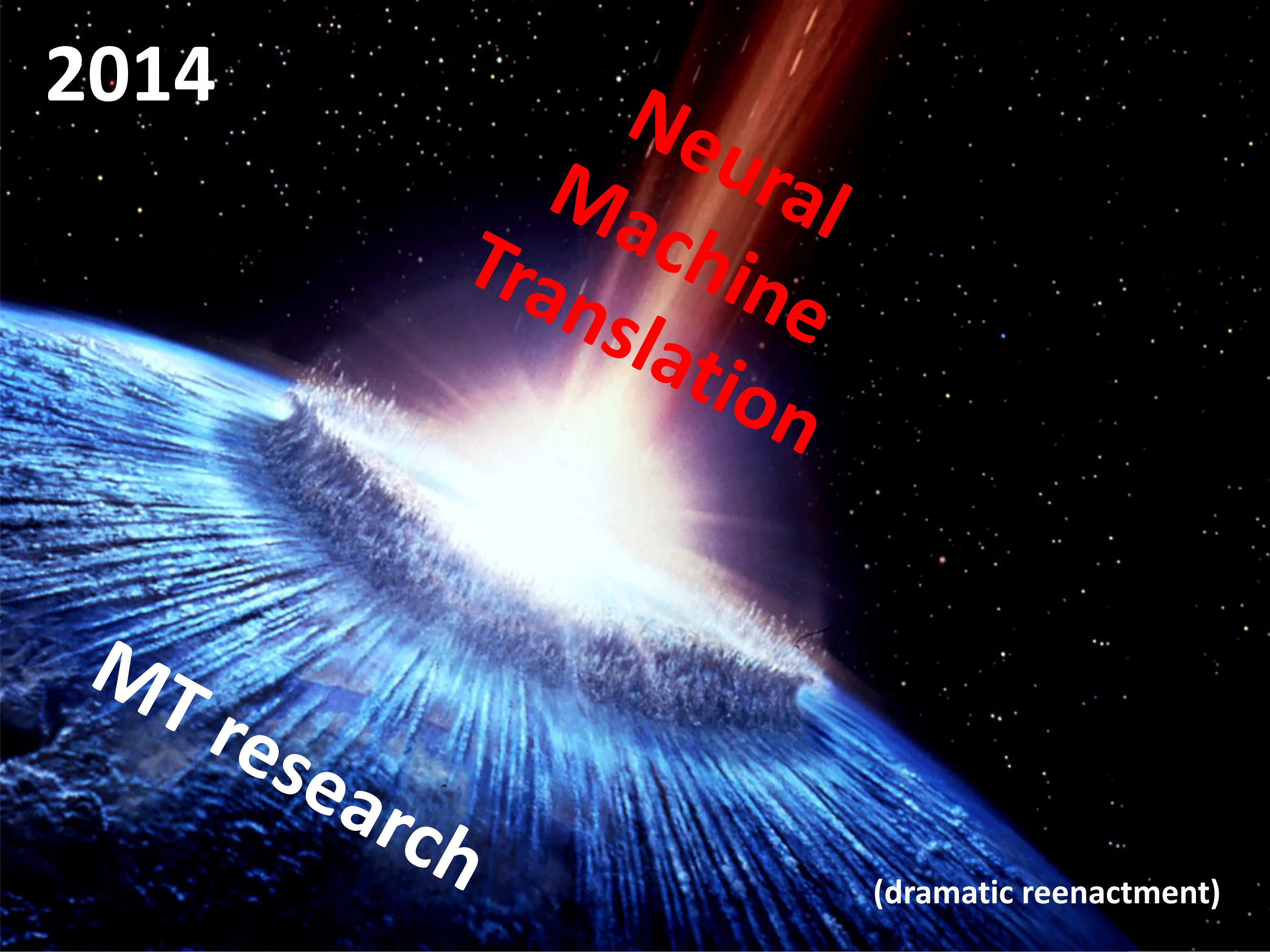


1990s-2010s: Statistical Machine Translation

- 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)

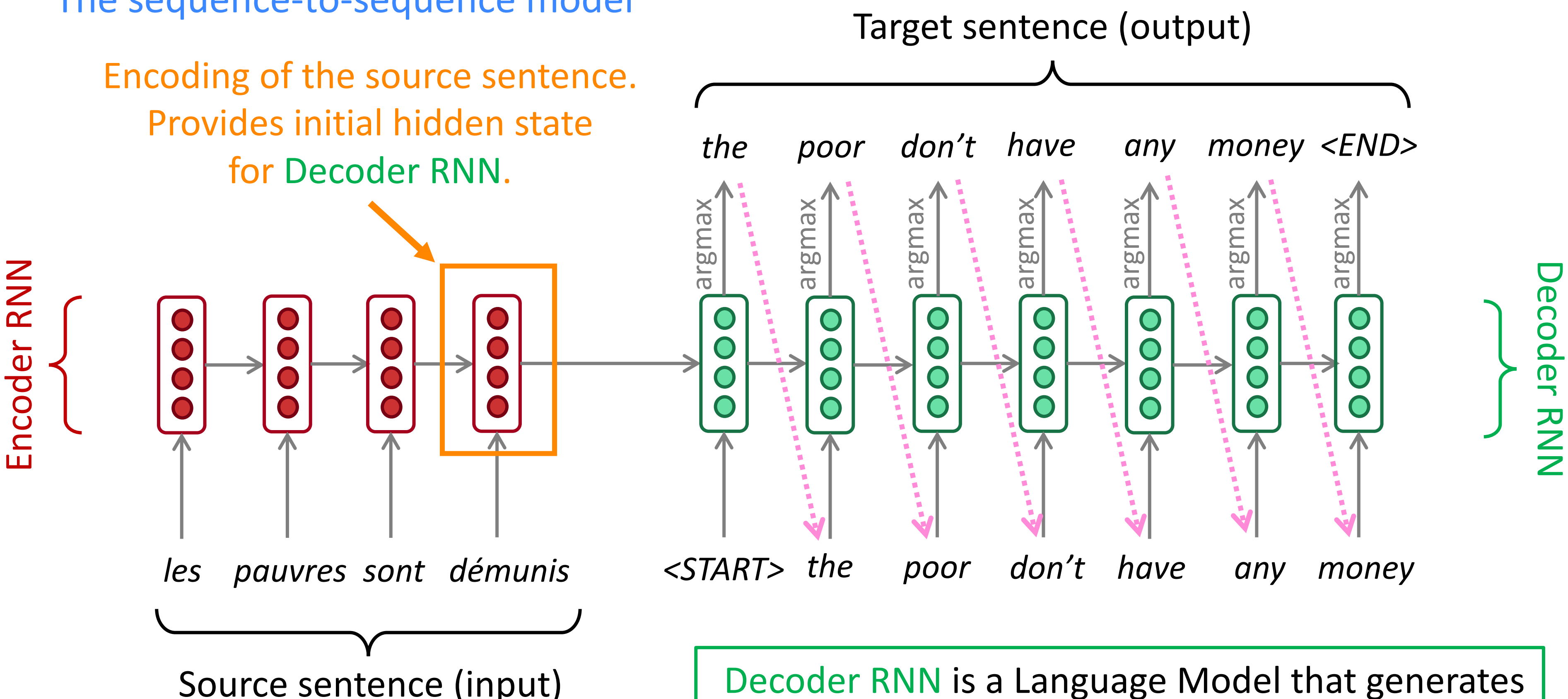
What is Neural Machine Translation?

- 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



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

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*

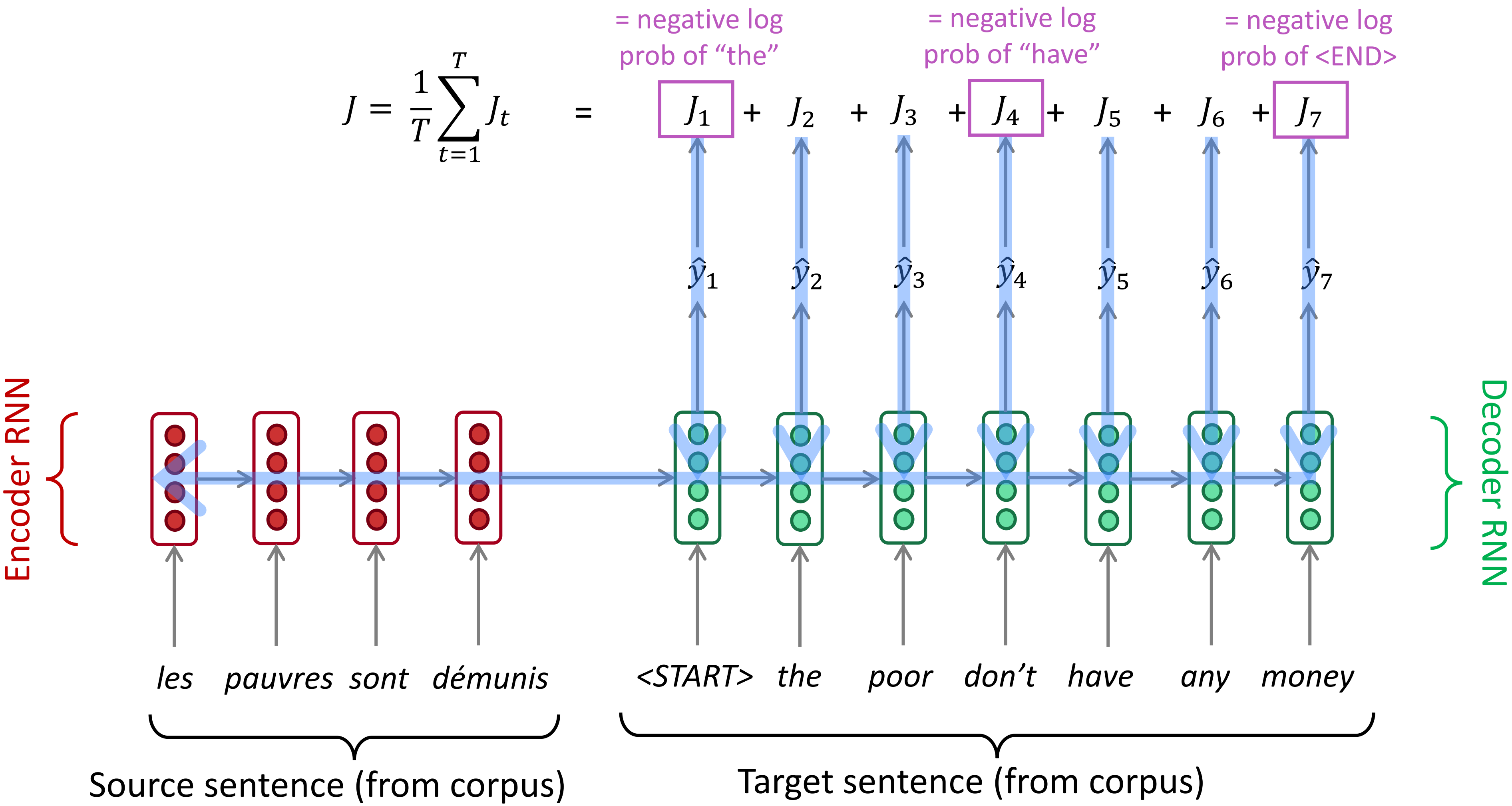
- NMT directly calculates $P(y|x)$:

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

Probability of next target word, given target words so far and source sentence *x*

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

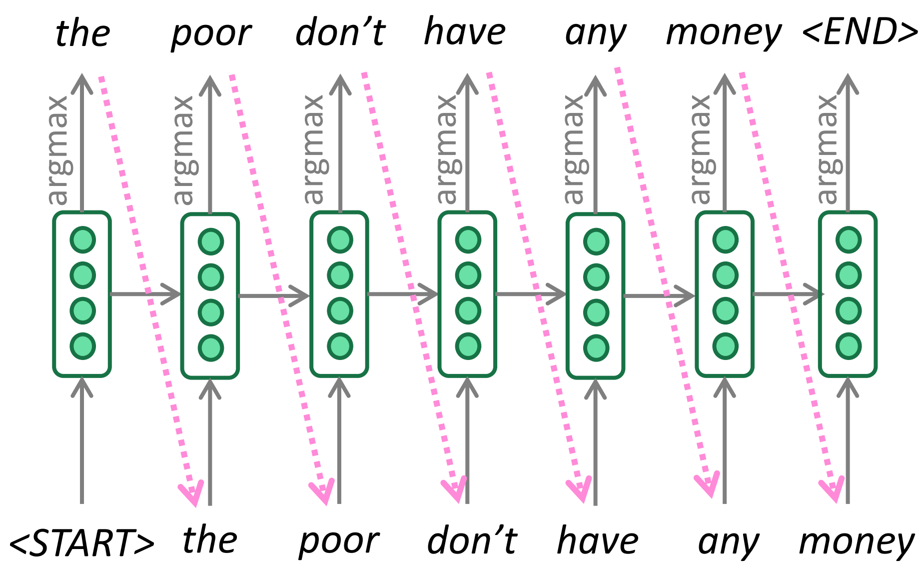
Training a Neural Machine Translation system



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)*
  - → *the* ____
  - → *the poor* ____
  - → *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!

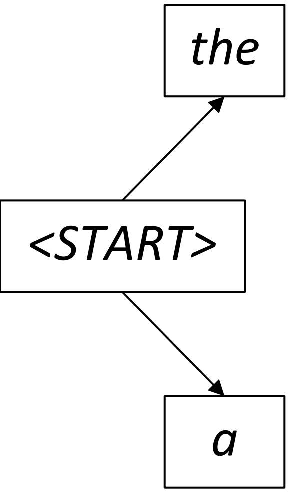
Beam search decoding: example

Beam size = 2

<START>

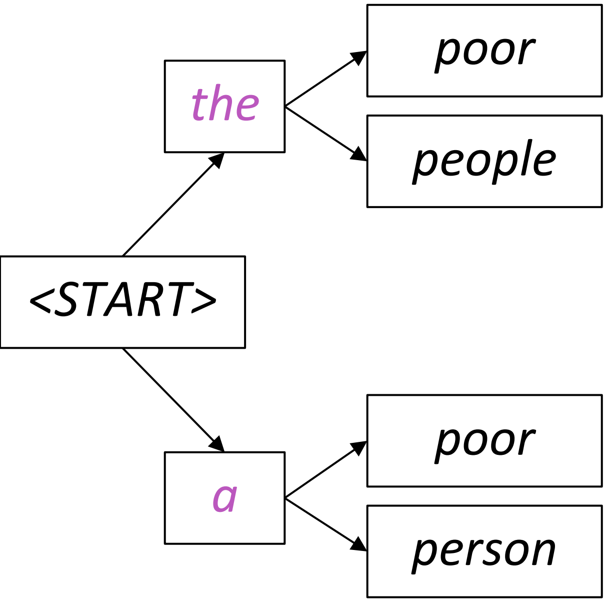
Beam search decoding: example

Beam size = 2



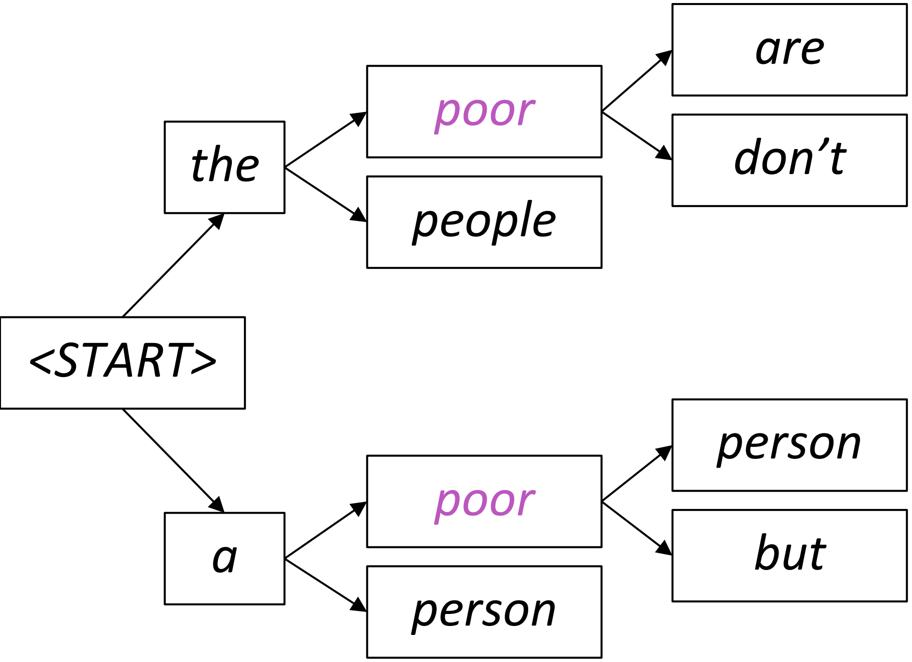
Beam search decoding: example

Beam size = 2



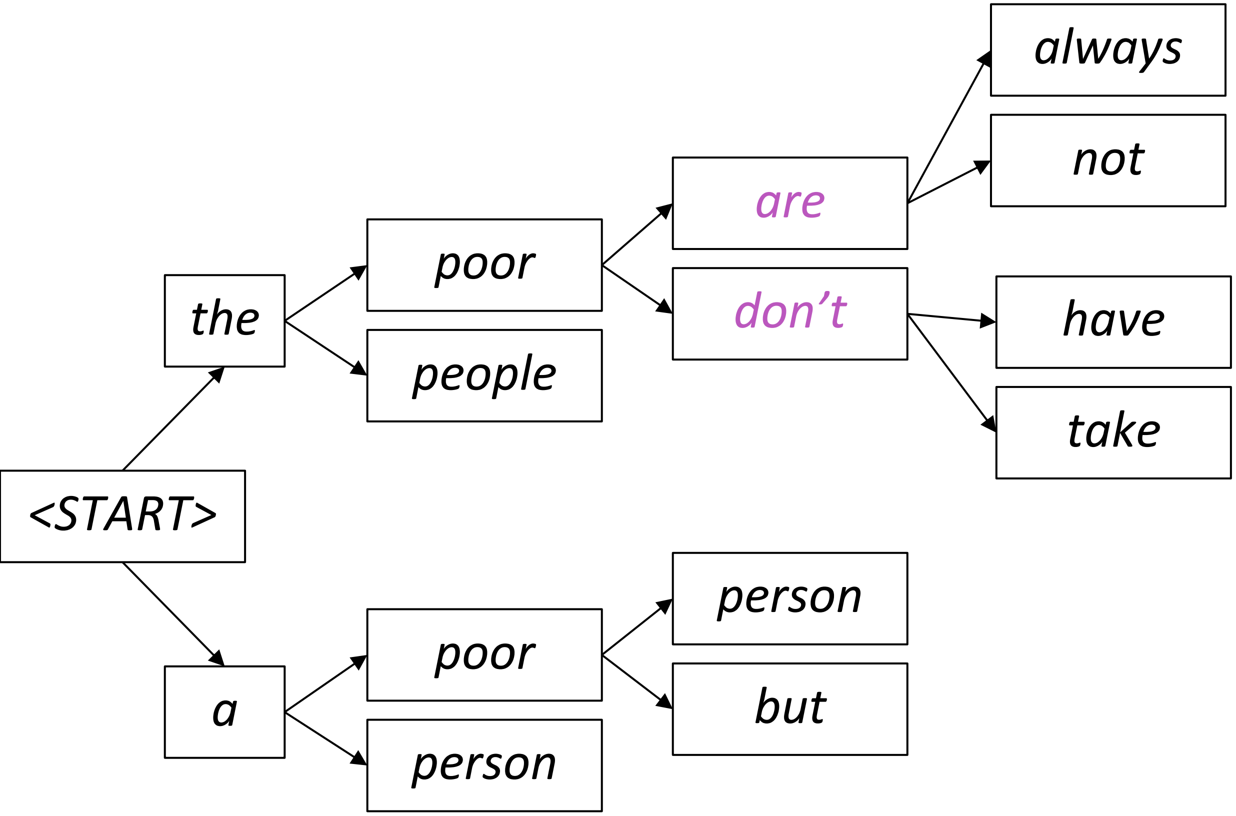
Beam search decoding: example

Beam size = 2



Beam search decoding: example

Beam size = 2



Beam search decoding: example

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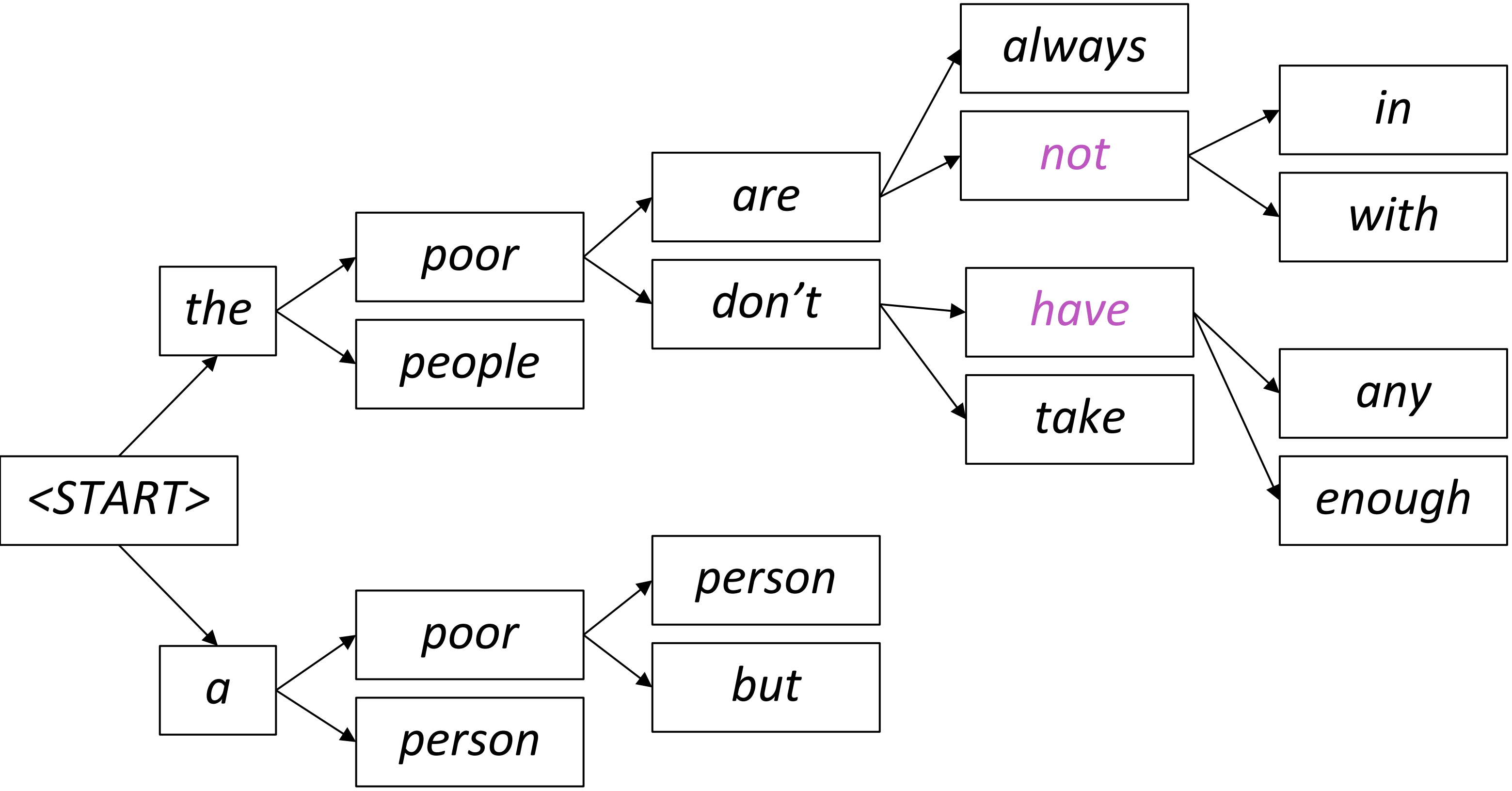

Beam search decoding: example

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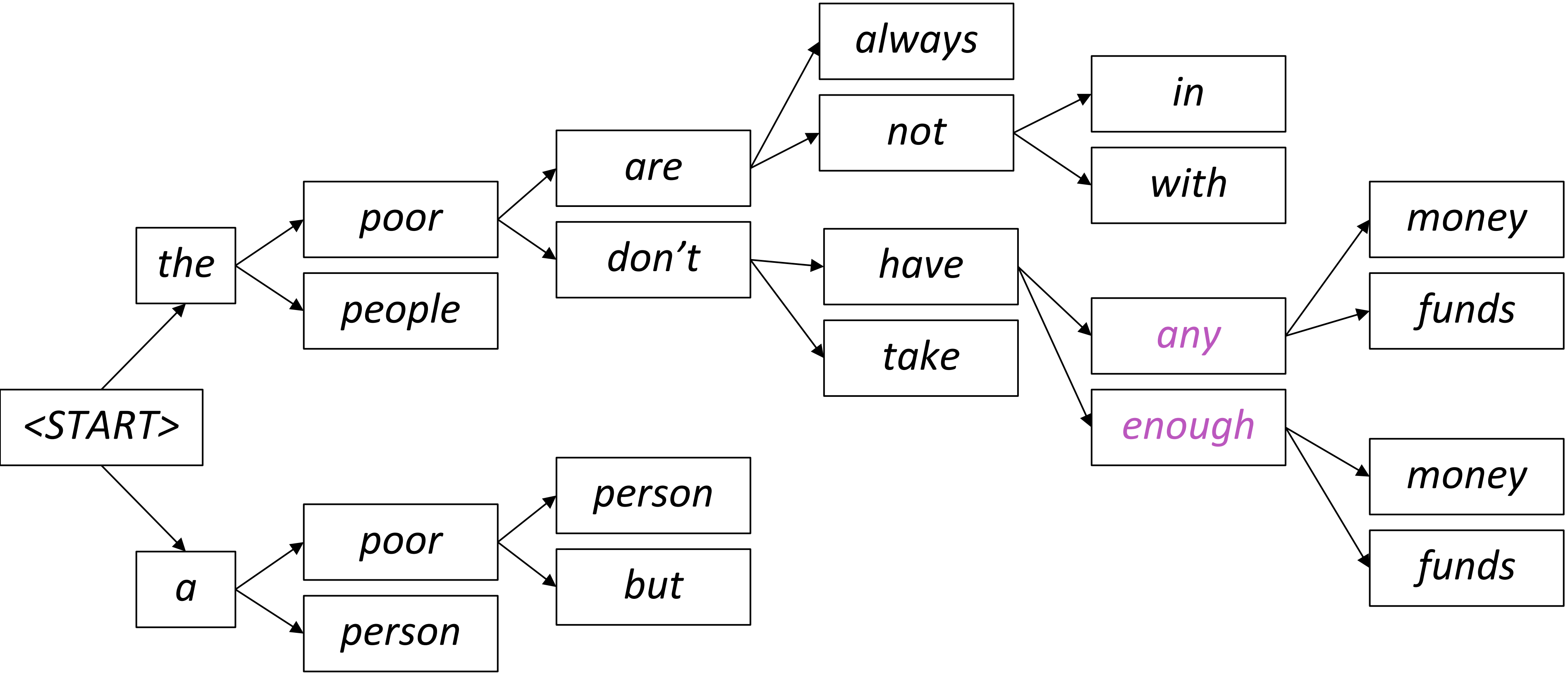
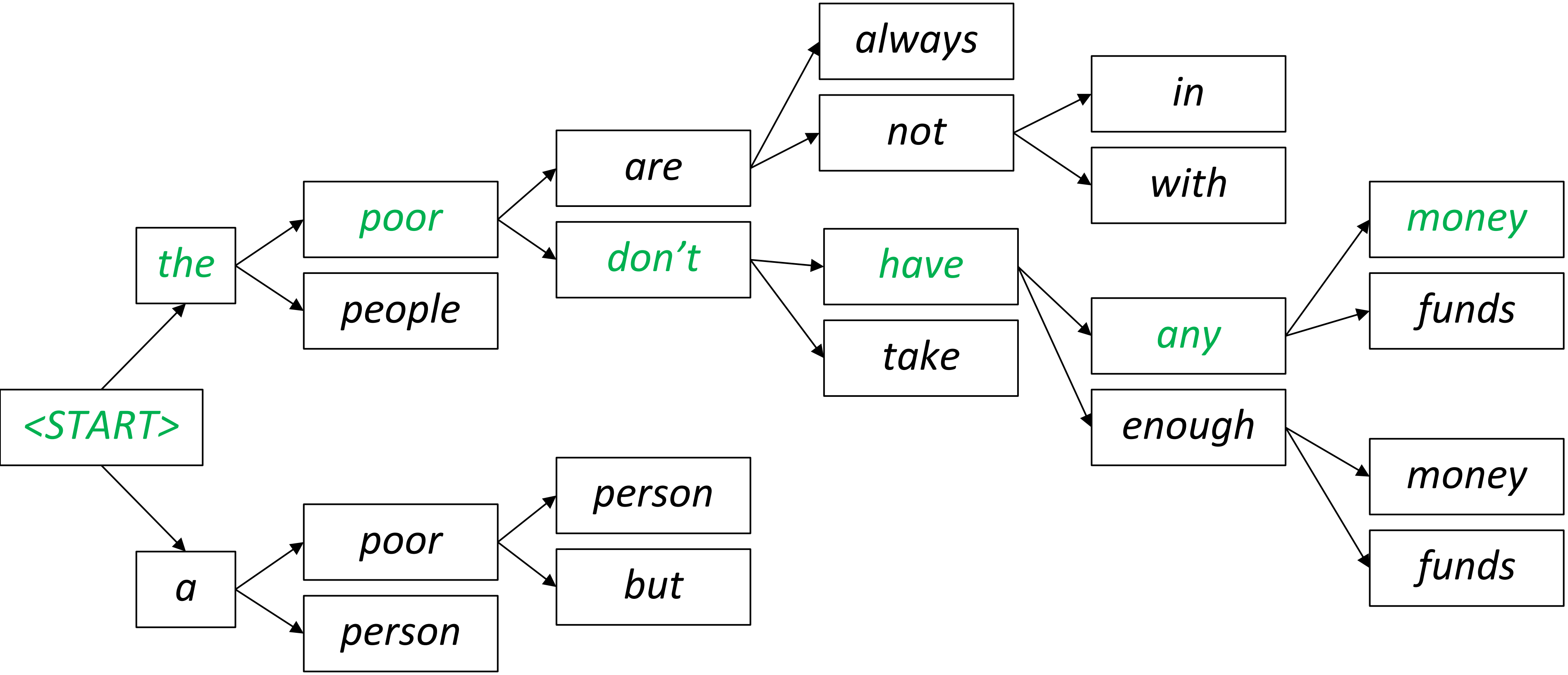


Beam search decoding: example

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!

How do we evaluate Machine Translation?

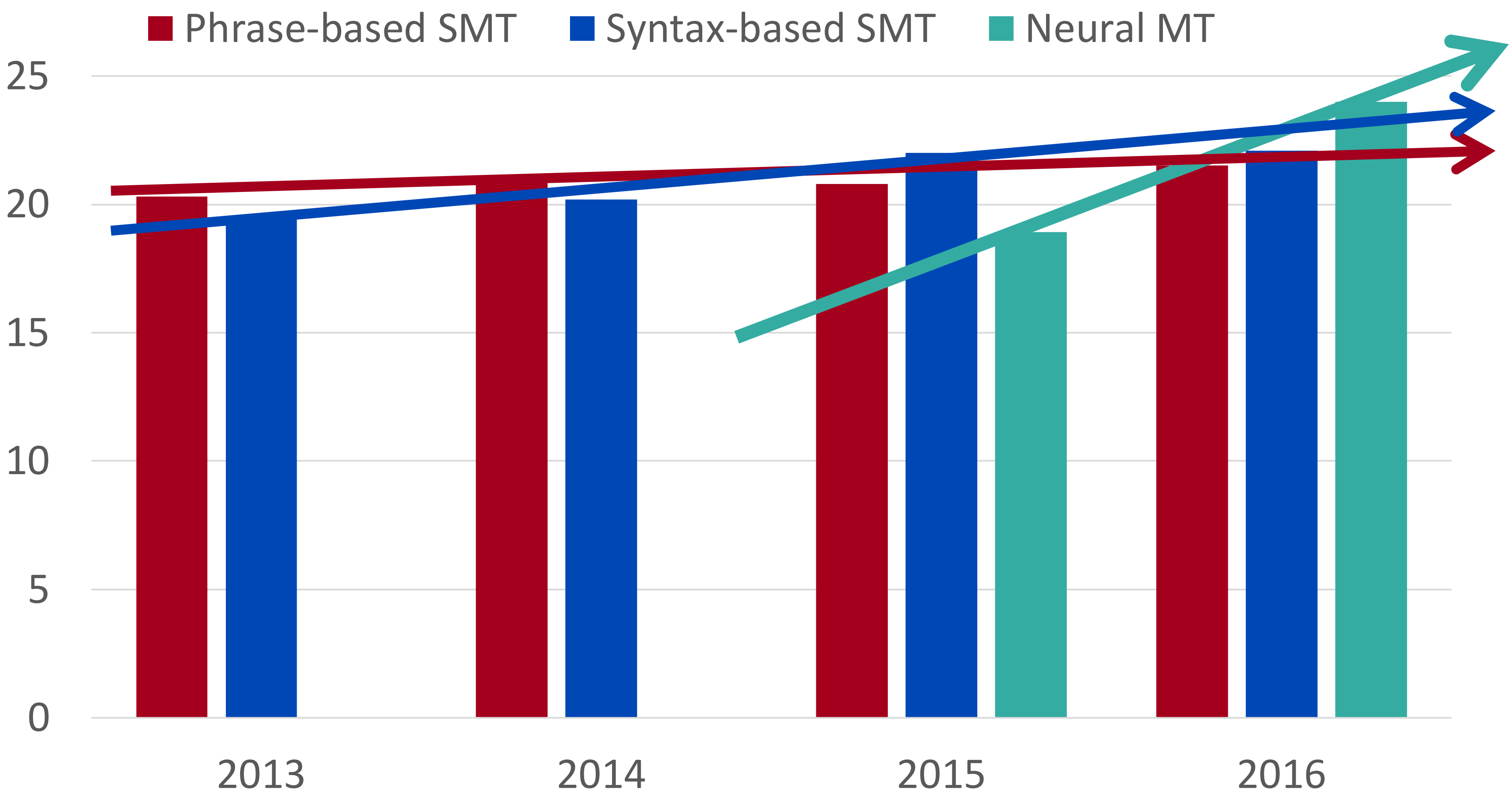
BLEU (**Bil**ingual **E**valuation **U**nderstudy)

- 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 ☹

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

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**

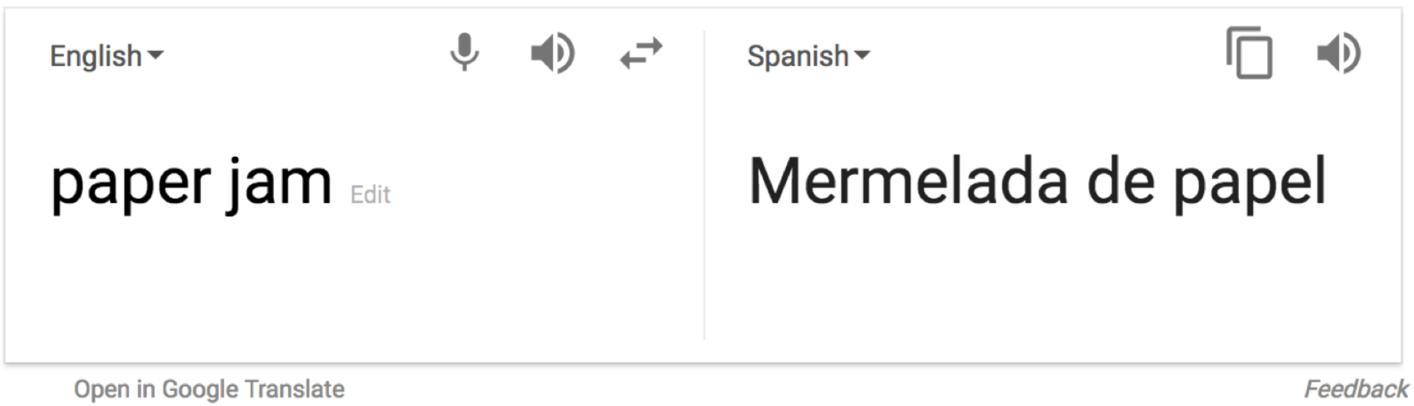
- **2014**: First seq2seq paper published
- **2016**: Google Translate switches from SMT to NMT
- This is amazing!
  - **SMT** systems, built by hundreds of engineers over many years, outperformed by NMT systems trained by a handful of engineers in a few months

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?

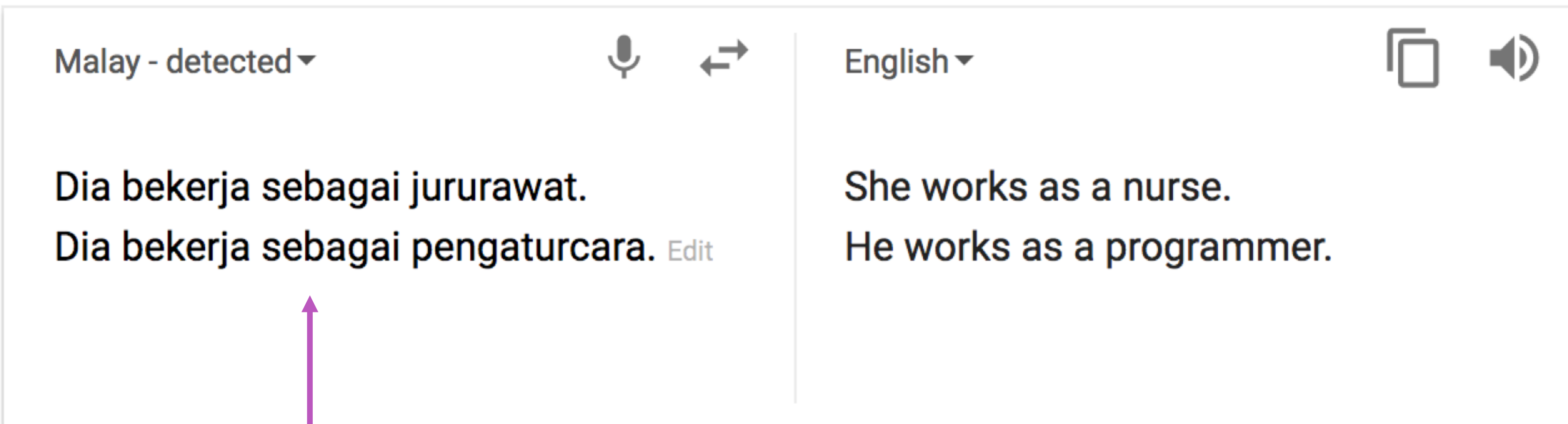
- **Nope!**
- Using common sense is still hard



?

So is Machine Translation solved?

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

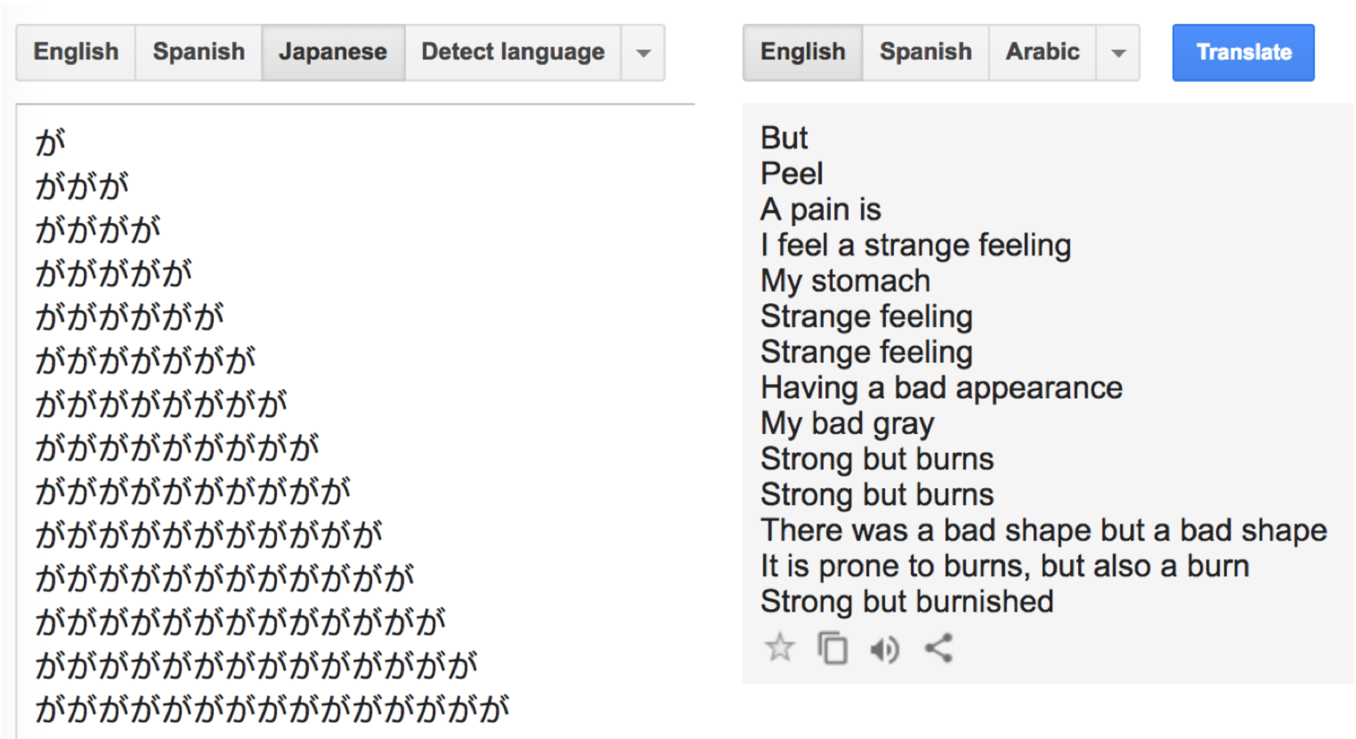


Didn’t specify gender

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

NMT research continues

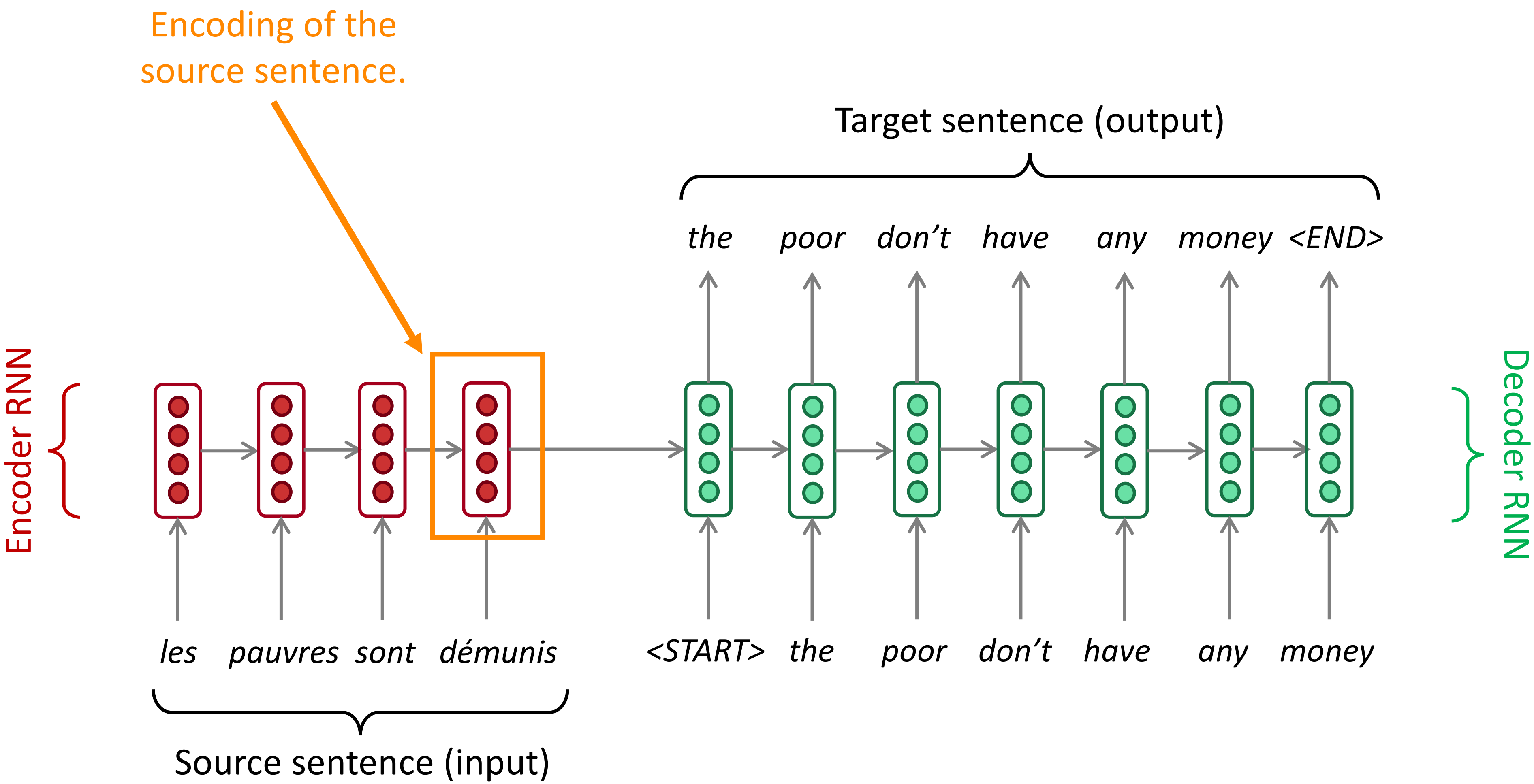
NMT is the **flagship task** for NLP Deep Learning

- 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…

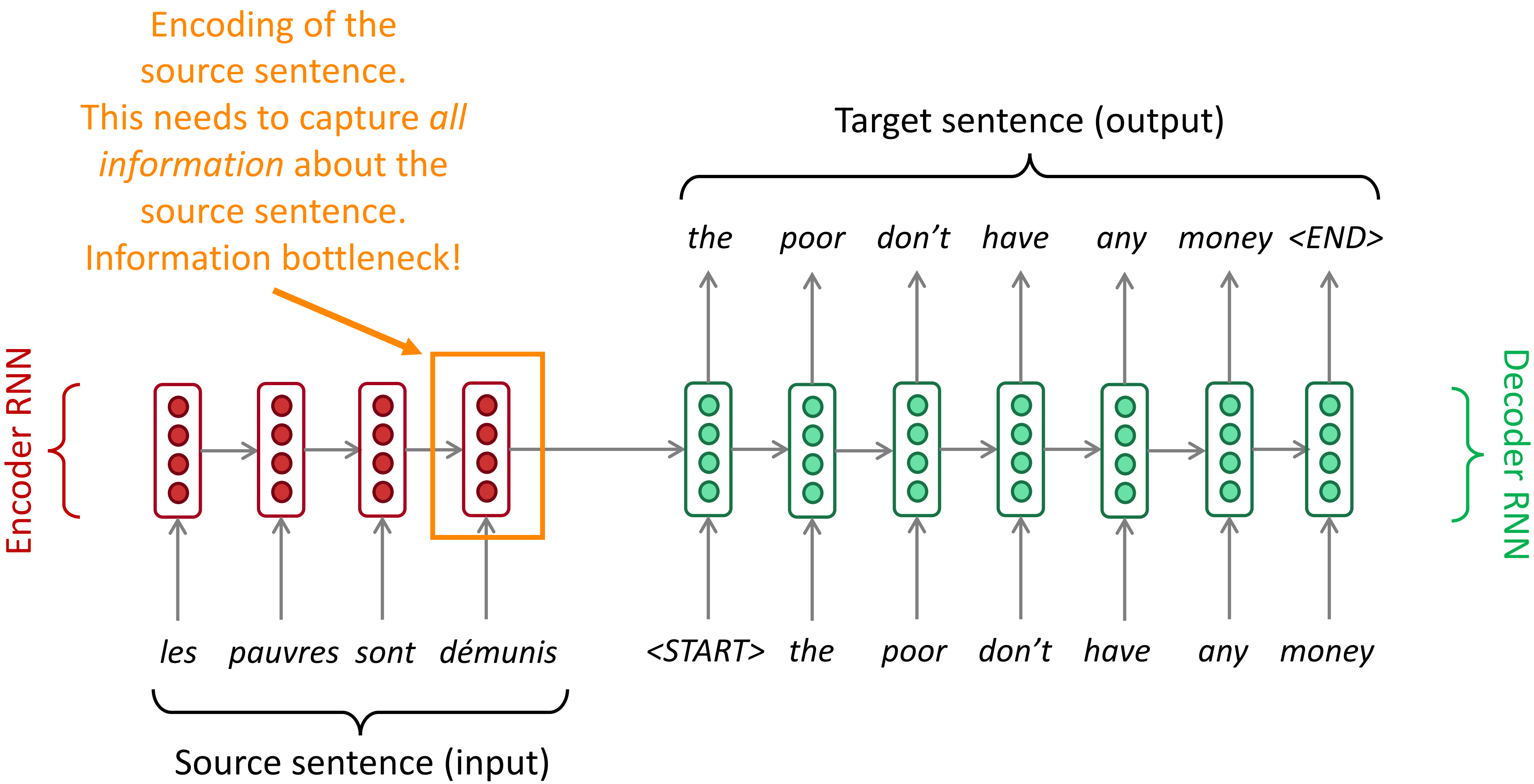
ATTENTION

Sequence-to-sequence: the bottleneck problem



Problems with this architecture?

Sequence-to-sequence: the bottleneck problem



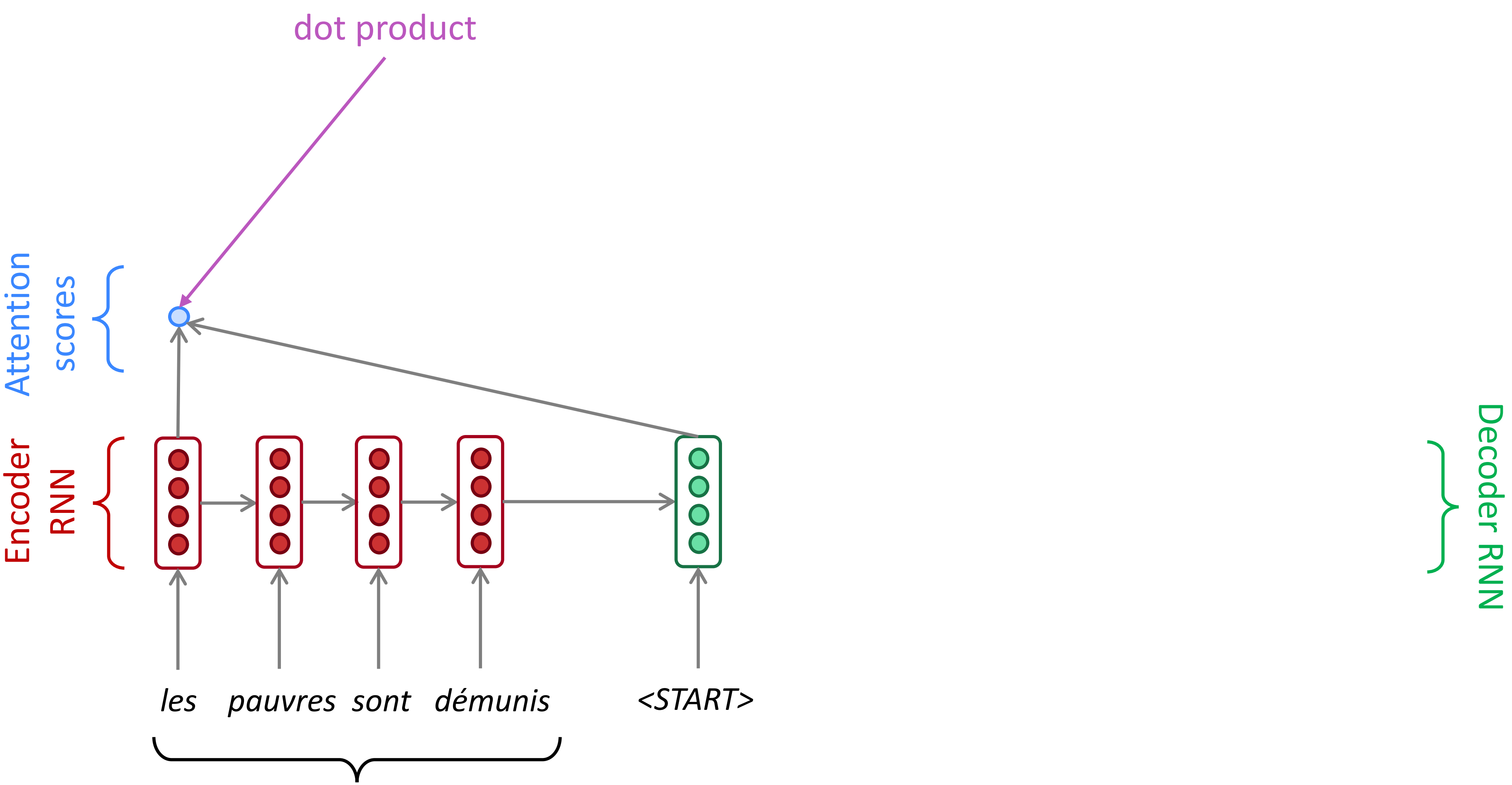
Attention

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

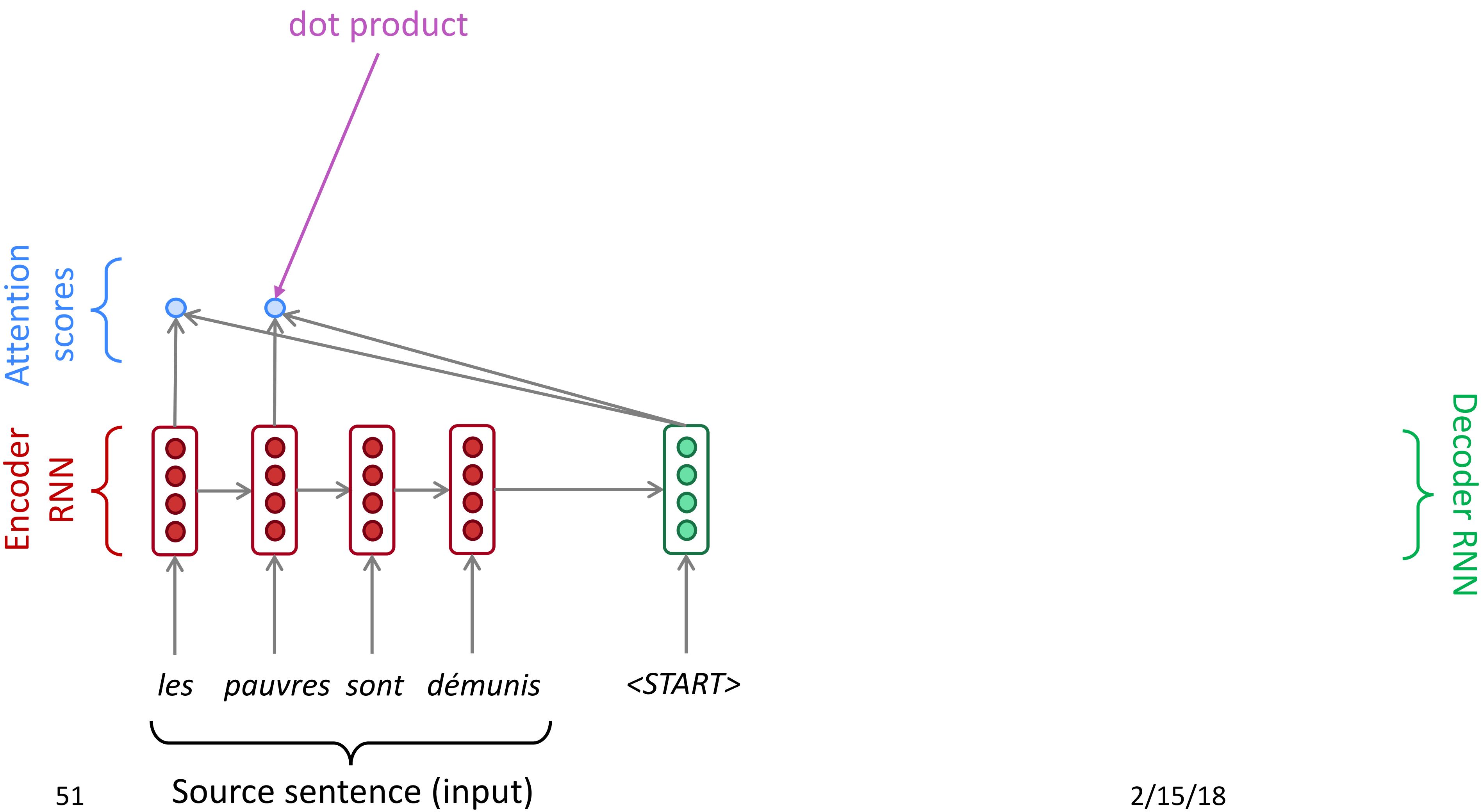
- Core idea: on each step of the decoder, *focus on a particular part* of the source sequence

- First we will show via diagram (no equations), then we will show with equations

Sequence-to-sequence with attention



Sequence-to-sequence with attention



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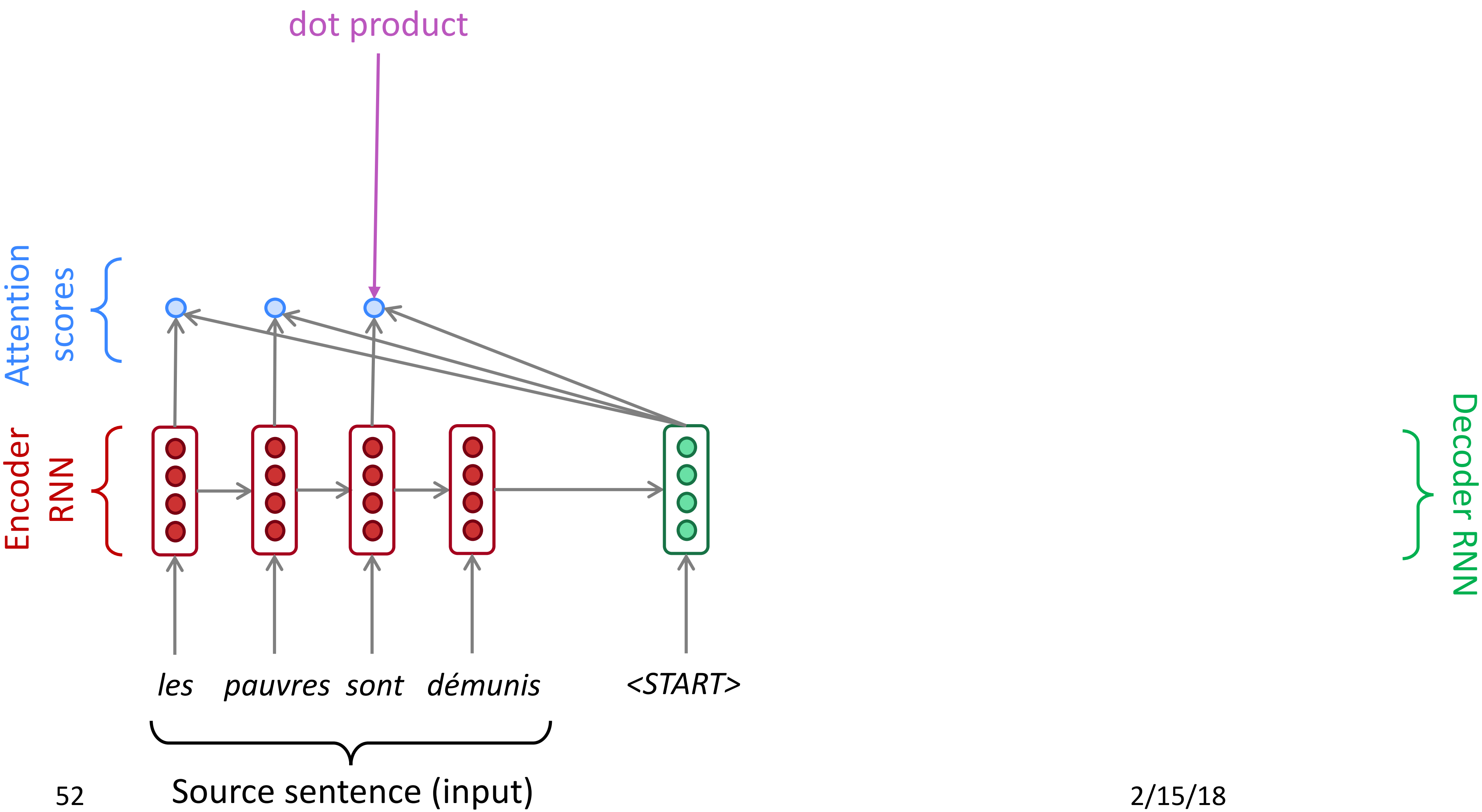

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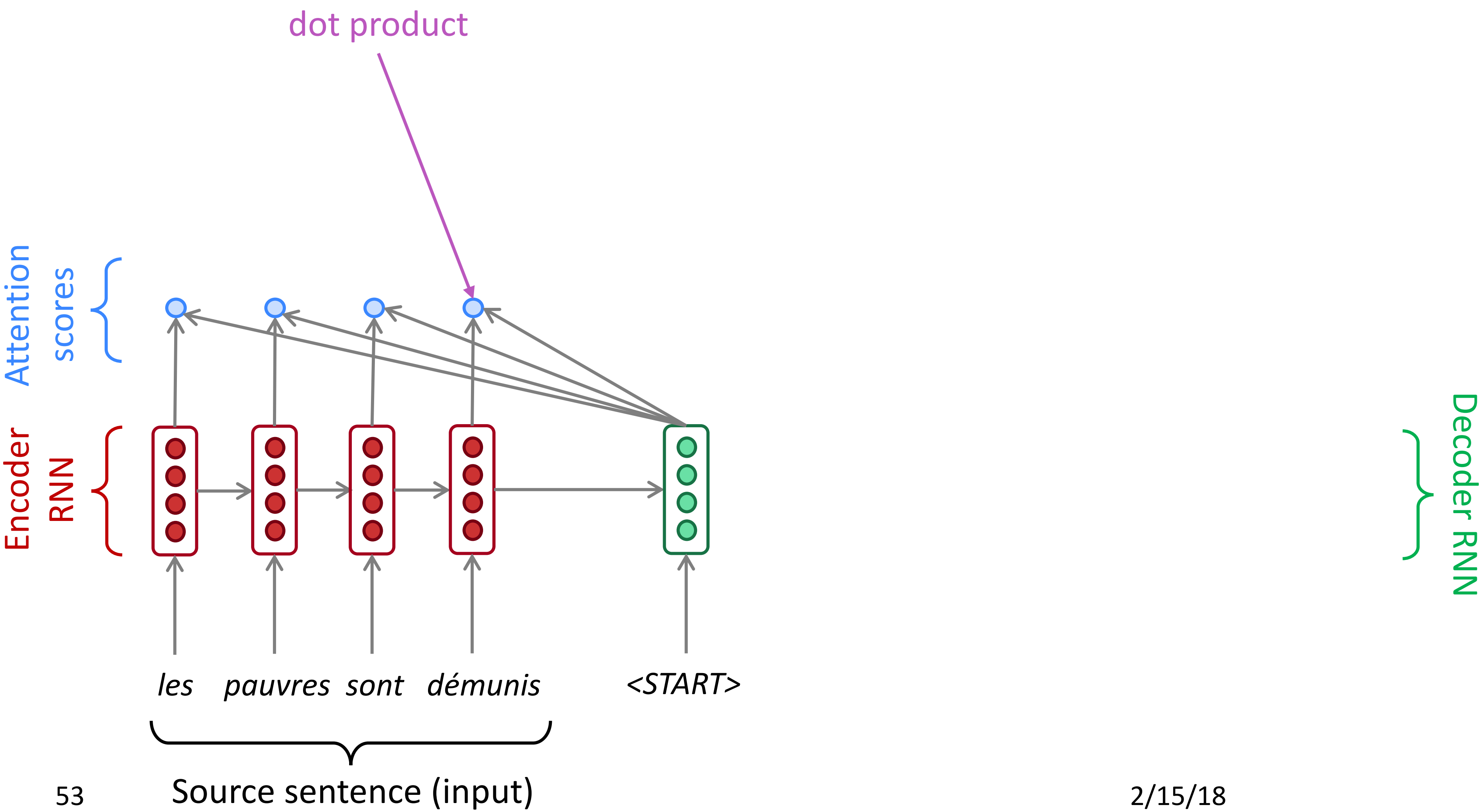

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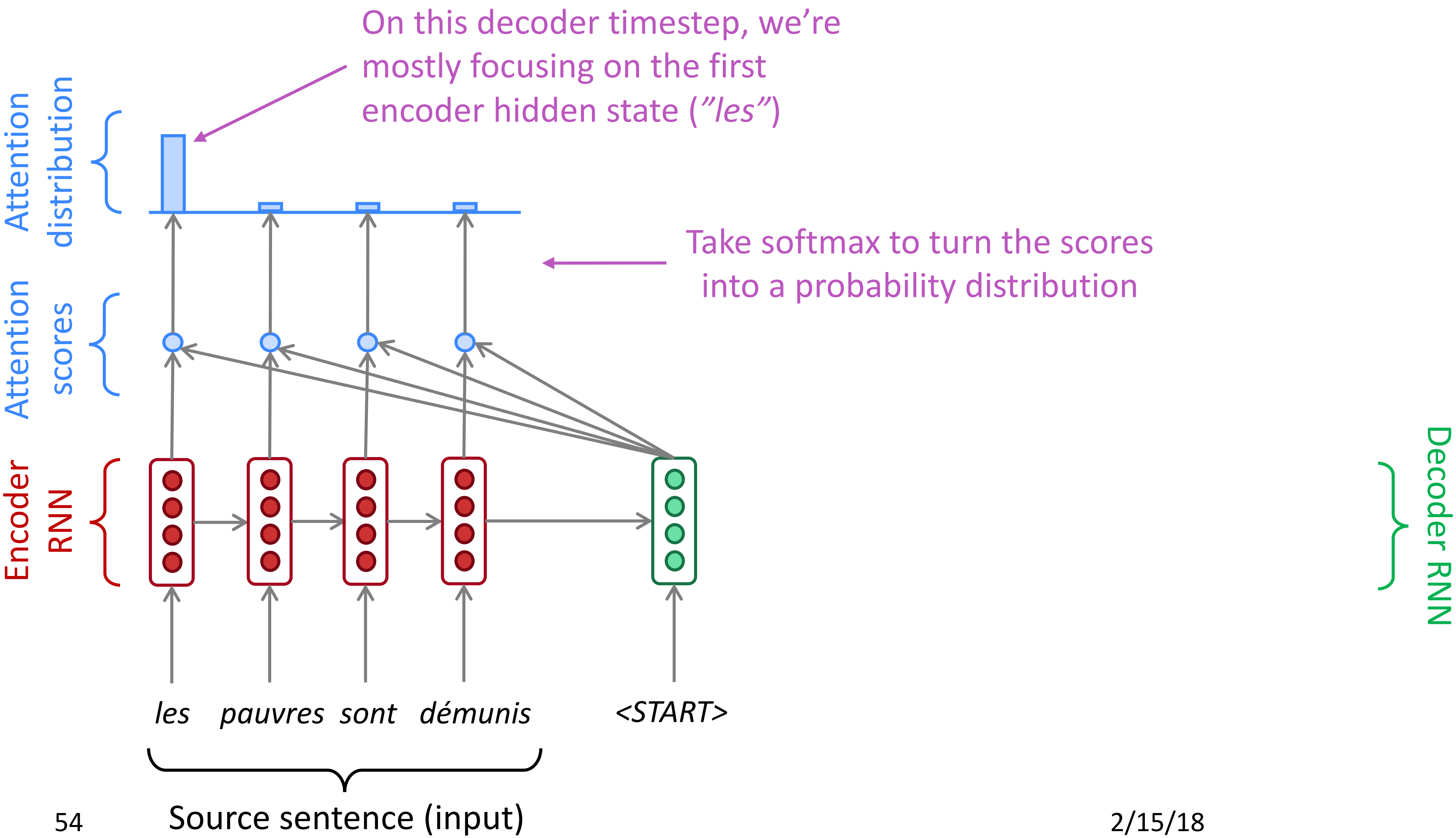
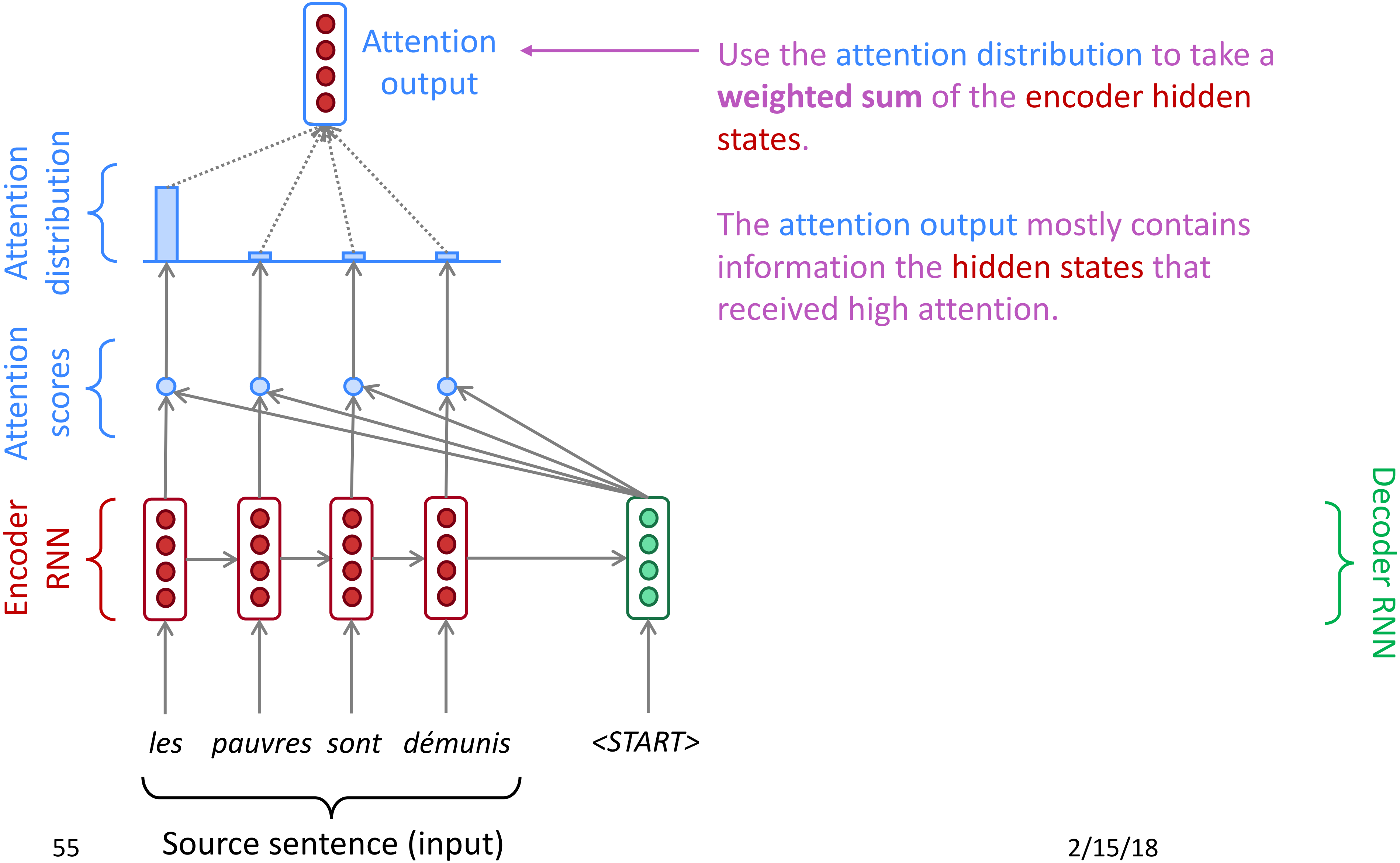


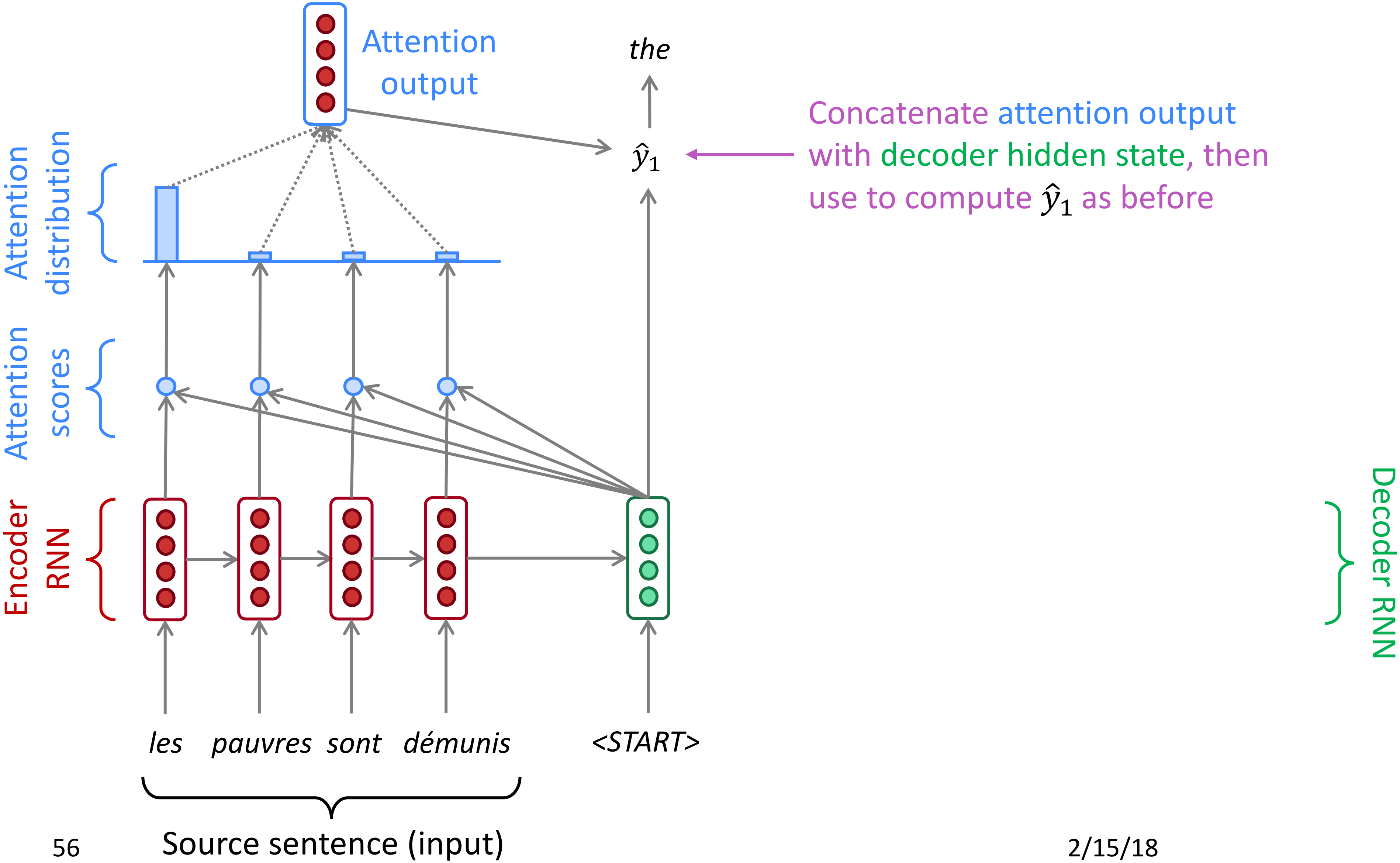
Sequence-to-sequence with attention



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

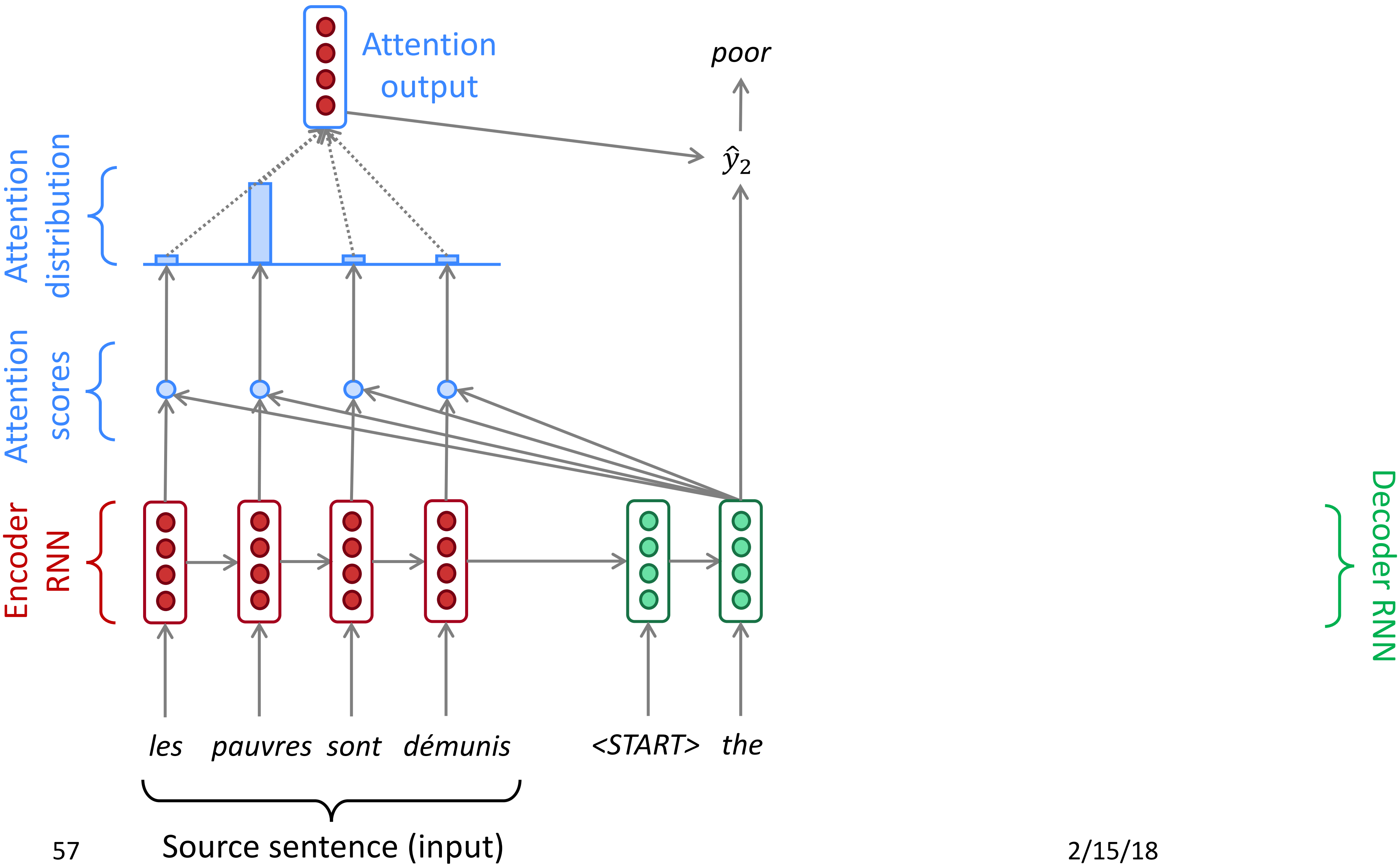
The attention output mostly contains information the hidden states that received high attention.

Sequence-to-sequence with attention



Concatenate attention output with decoder hidden state, then use to compute $\hat{y}_1$ as before

Sequence-to-sequence with attention



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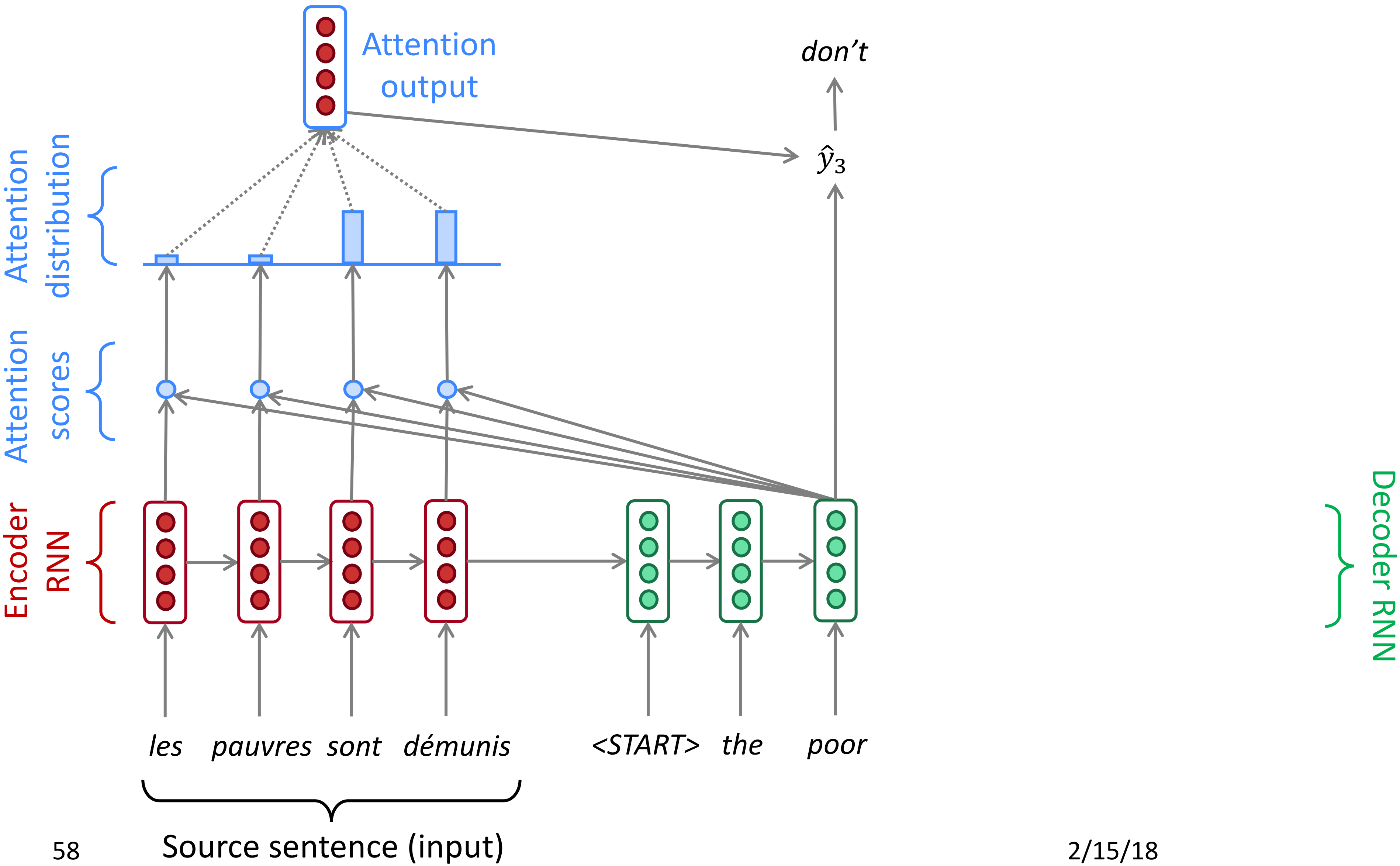

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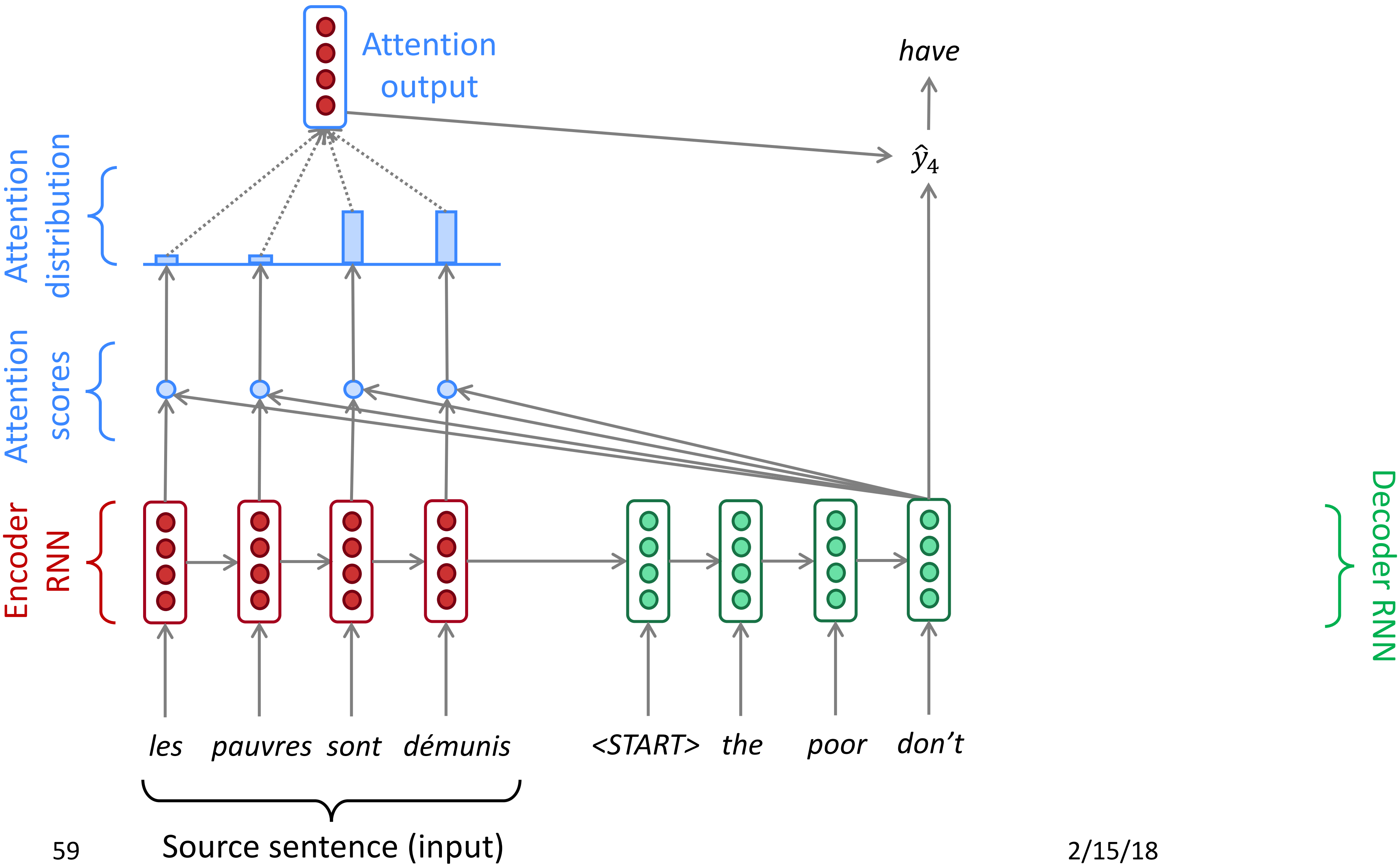

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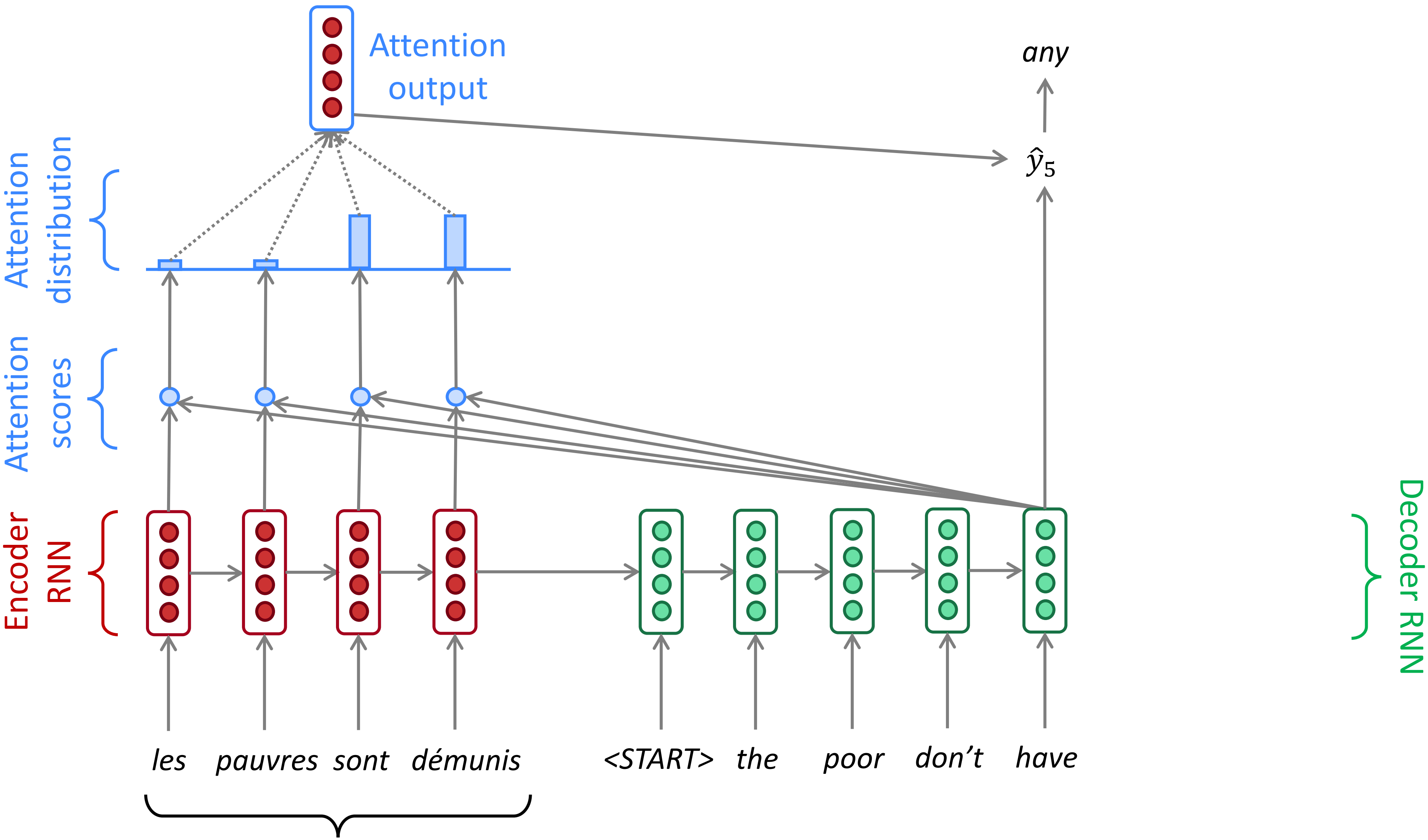
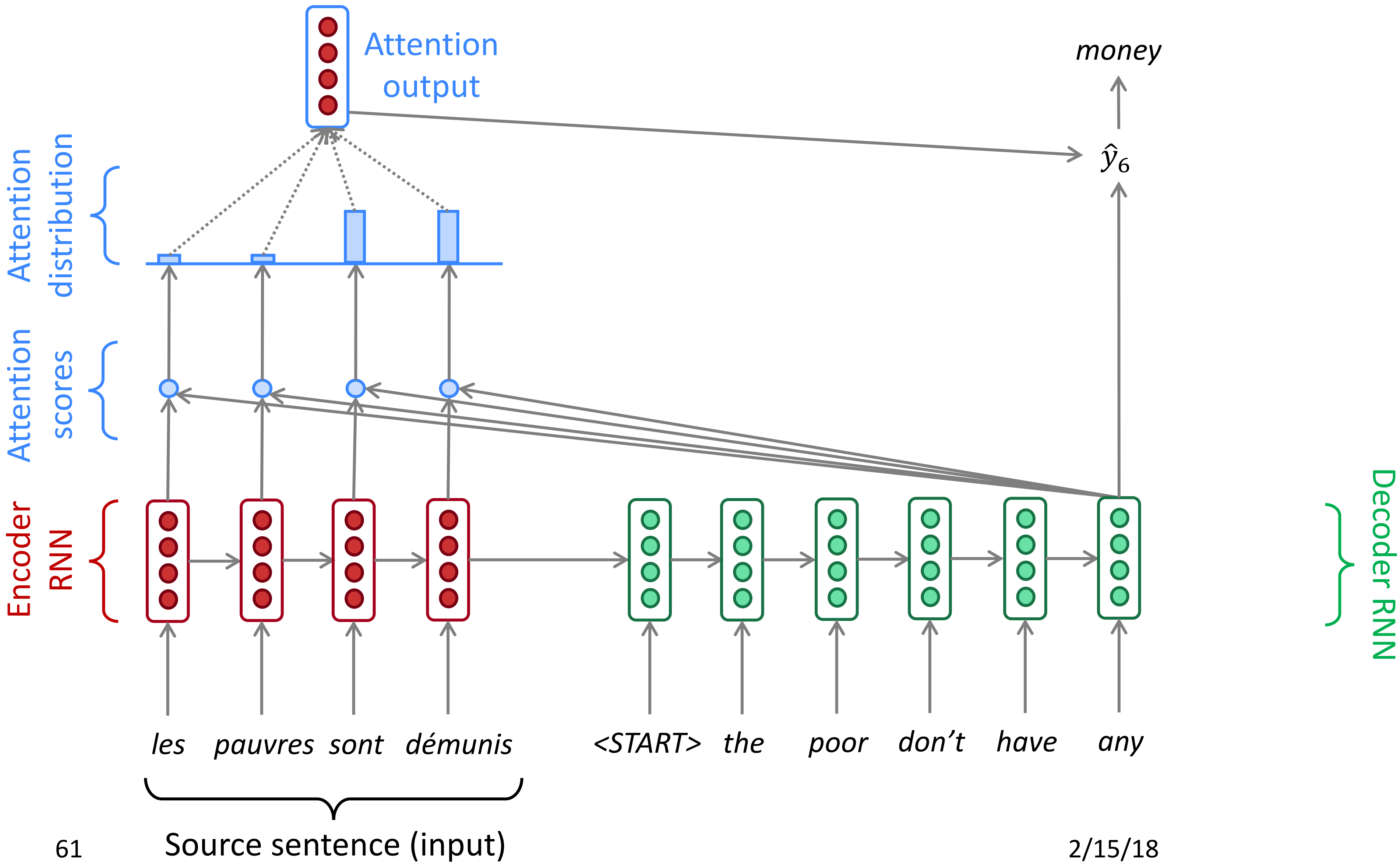


Sequence-to-sequence with attention



Attention: in equations

encoder hidden state - [h1, … , hN]
decoder hidden state - st

et = [encoder state * decoder state]
alphat =. softmax(et)
at = [alphat *ht]
- decoder state가 encoder state의 어디를 봐야 하는지 encoding 한다.

at와 st를 함께 넣어줘서 prediction 한다.

- 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)

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

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

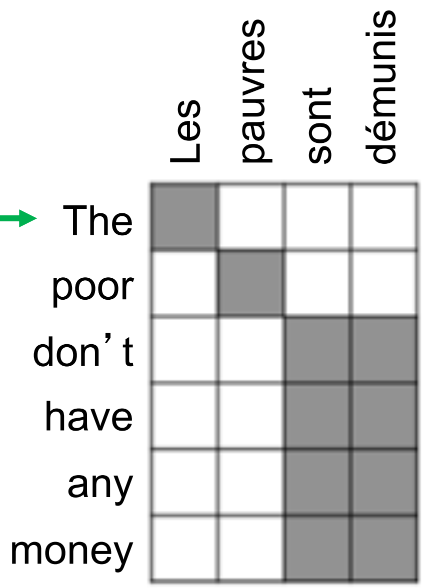
$$\boldsymbol{a}_t = \sum_{i=1}^N \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

- 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

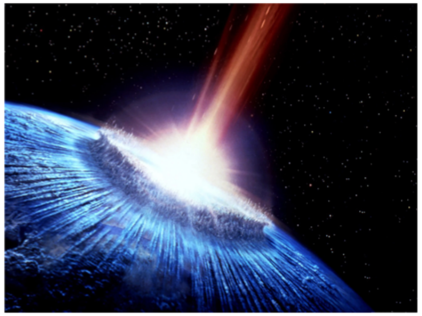
- Attention significantly improves NMT performance
  - It's very useful to allow decoder to focus on certain parts of the source
- Attention solves the bottleneck problem
  - Attention allows decoder to look directly at source; bypass bottleneck
- Attention helps with vanishing gradient problem
  - Provides 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 → short text)
  - Dialogue (previous utterances → next utterance)
  - Parsing (input text → output parse as sequence)
  - Code generation (natural language → Python code)

Next time

- More types of attention
- More uses for attention
- More advanced sequence-to-sequence techniques