Natural Language Processing with Deep Learning

CS224N/Ling284

Machine Translation,
Sequence-to-sequence and Attention

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Overview

- Introduce a new task: Machine Translation

is a major use-case of

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

is improved by

- Introduce a new neural technique: attention

Section 1: Pre-Neural Machine Translation

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*

\- Rousseau

1950s: Early Machine Translation

Machine Translation research began in the early 1950s.

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

1 minute video showing 1954 MT:
https://youtu.be/K-HfpsHPmvw

- Systems were mostly rule-based, using a bilingual dictionary to map Russian words to their English counterparts

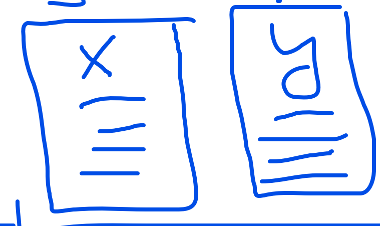
1990s-2010s: Statistical Machine Translation

- Core idea: Learn a probabilistic model from data
- Suppose we're translating French → English.

  x y
- We want to find best English sentence y, given French sentence x

  S T

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



- 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 (*fidelity*). Learnt from parallel data.

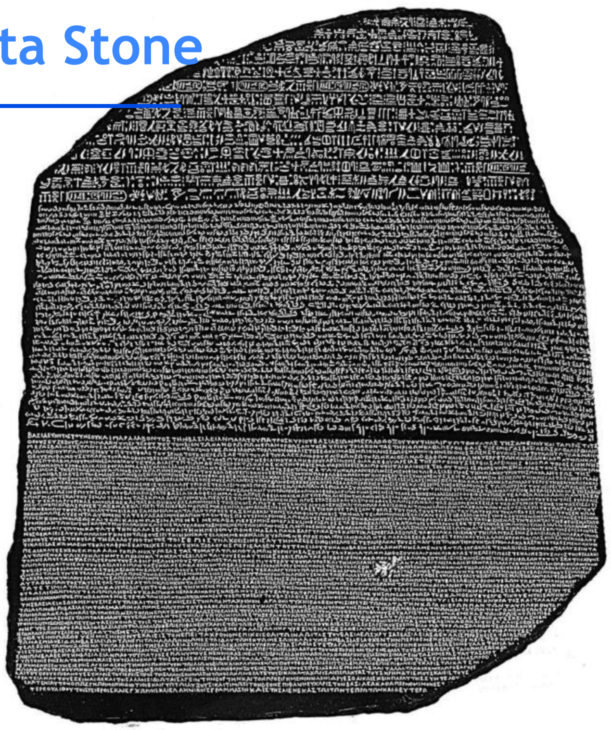
Language Model

Models how to write good English (*fluency*). 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



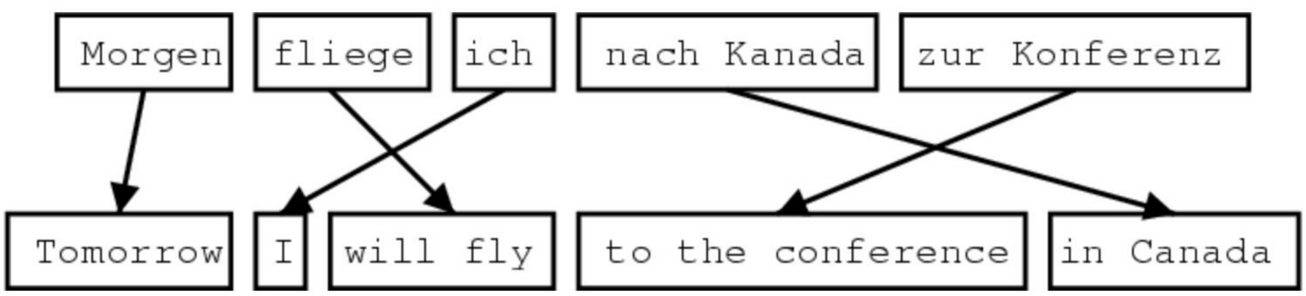
Learning alignment for SMT

- Question: How to learn translation model $P(x|y)$ from the parallel corpus?

- Break it down further: Introduce latent a variable into the model:

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

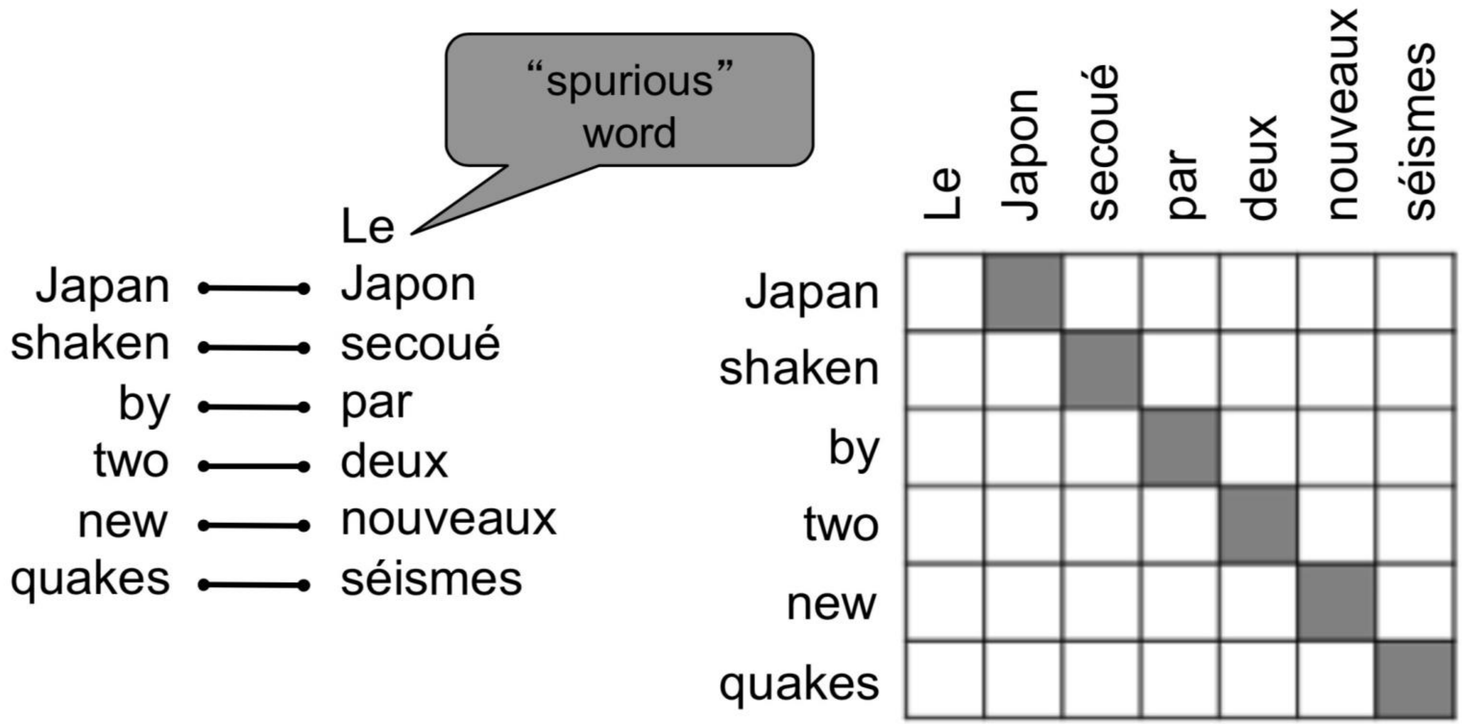
where *a* is the alignment, i.e. word-level correspondence between source sentence *x* and target sentence *y*



What is alignment?

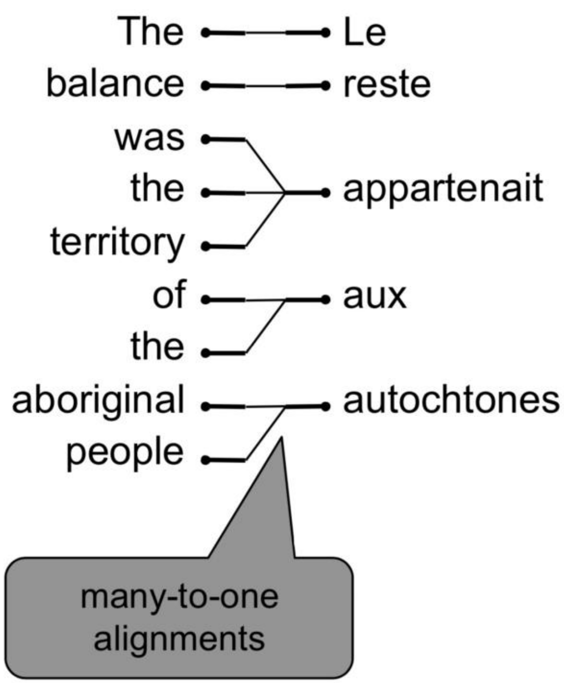
Alignment is the correspondence between particular words in the translated sentence pair.

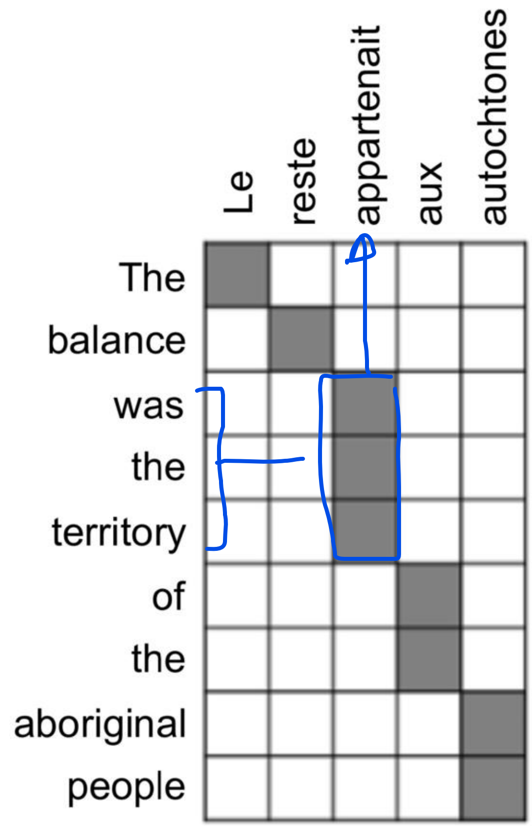
- Typological differences between languages lead to complicated alignments!
  - Note: Some words have no counterpart



Examples from: "The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993.
http://www.aclweb.org/ anthology/J93-2003

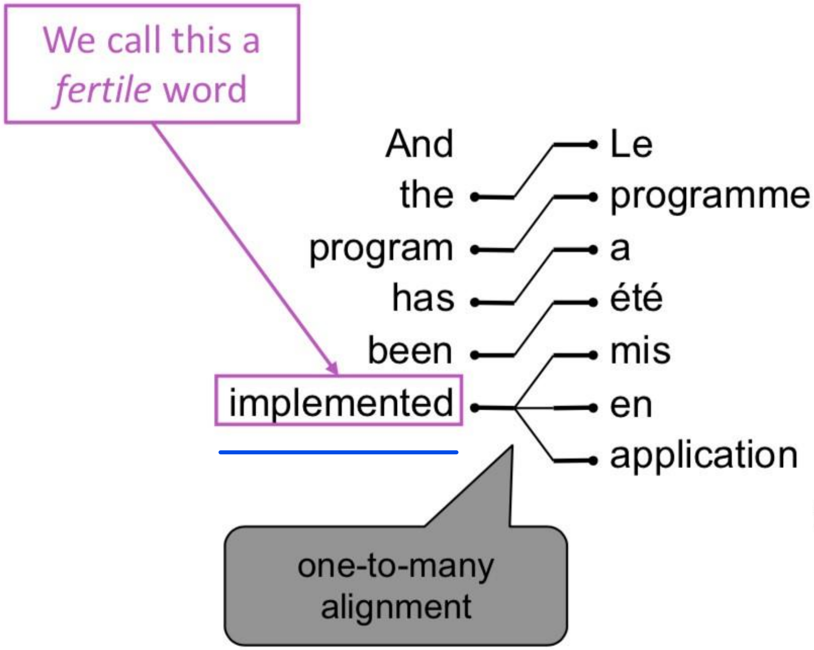
Alignment can be many-to-one

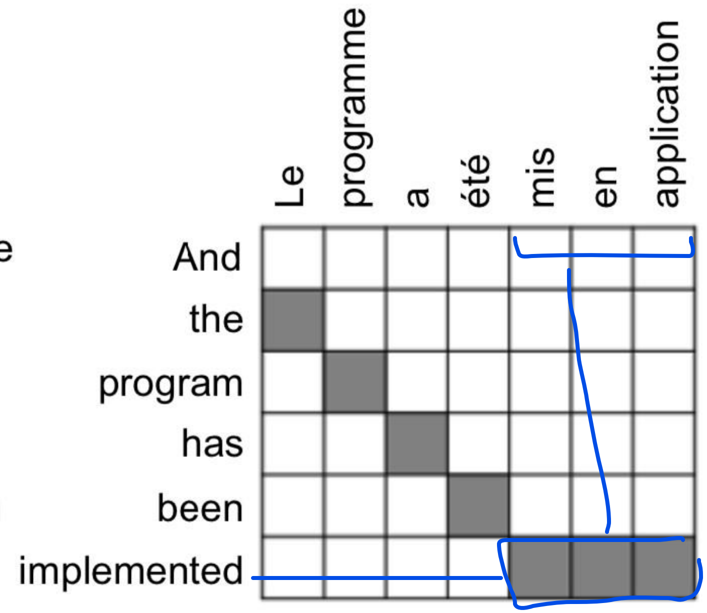




Examples from: "The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993. http://www.aclweb.org/ anthology/J93-2003

Alignment can be one-to-many

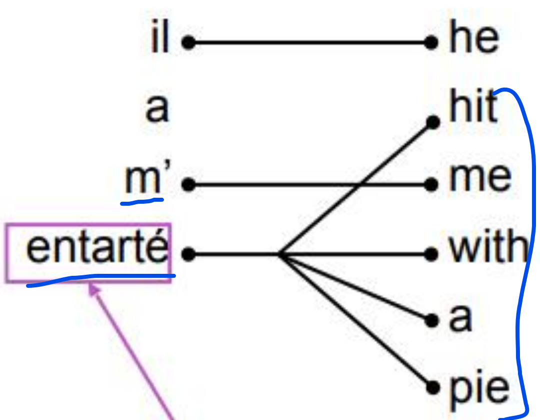




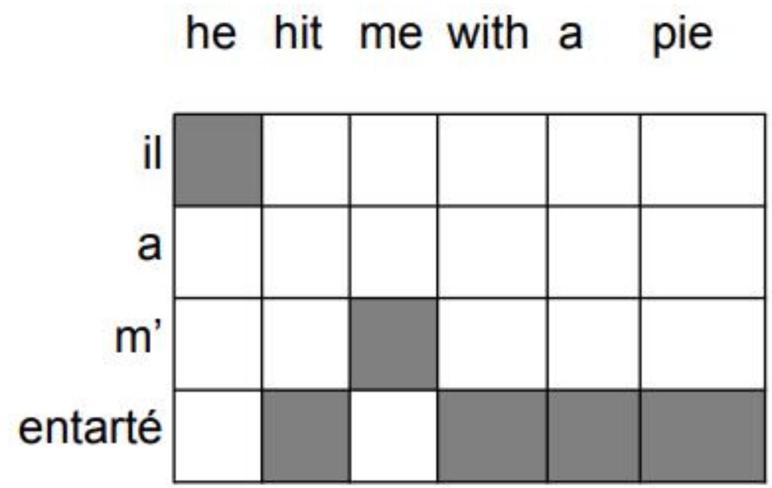
Examples from: “The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993. http://www.aclweb.org/ anthology/J93-2003

Alignment is complex

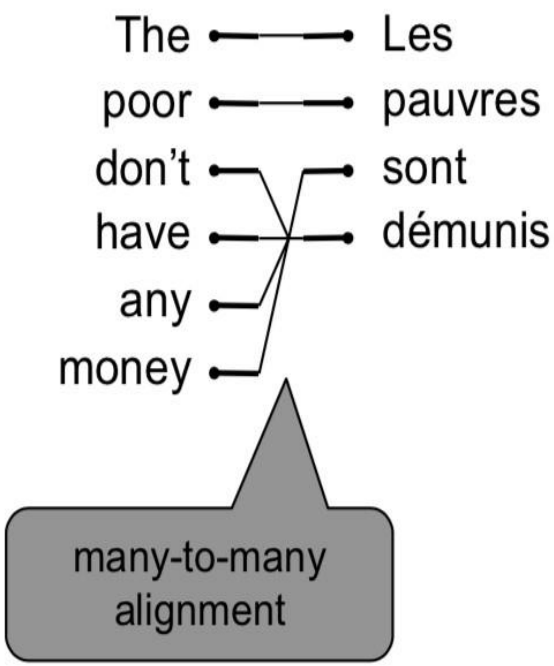
Some words are very fertile!

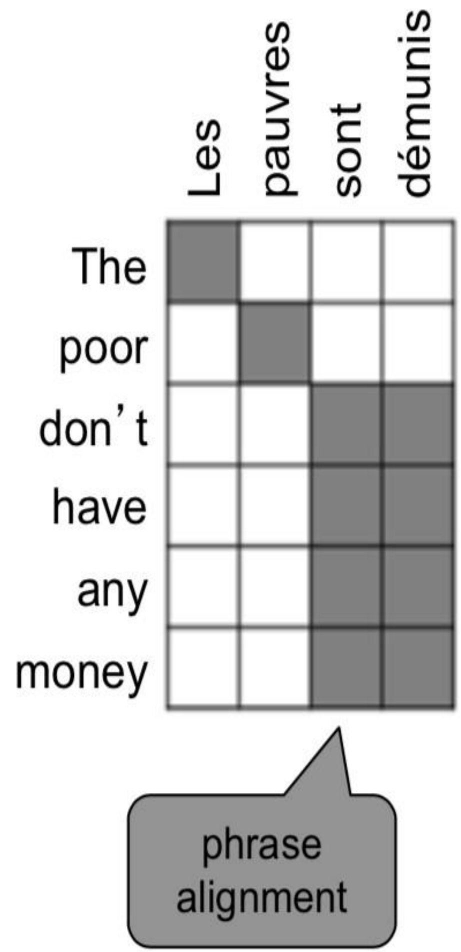


This word has no single-word equivalent in English



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





Examples from: "The Mathematics of Statistical Machine Translation: Parameter Estimation", Brown et al, 1993. http://www.aclweb.org/ anthology/J93-2003

Learning alignment for SMT

- We learn $P(x, a|y)$ as a combination of many factors, including:
  - Probability of particular words aligning (also depends on position in sent)
  - Probability of particular words having particular fertility (number of corresponding words)
  - etc.
- Alignments *a* are latent variables: They aren't explicitly specified in the data!
    - Require the use of special learning aglos (like ExpectationMaximization) for learning the parameters of distributions with latent variables

EM

Decoding for MT

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

Question:
How to compute this argmax?

Translation Model

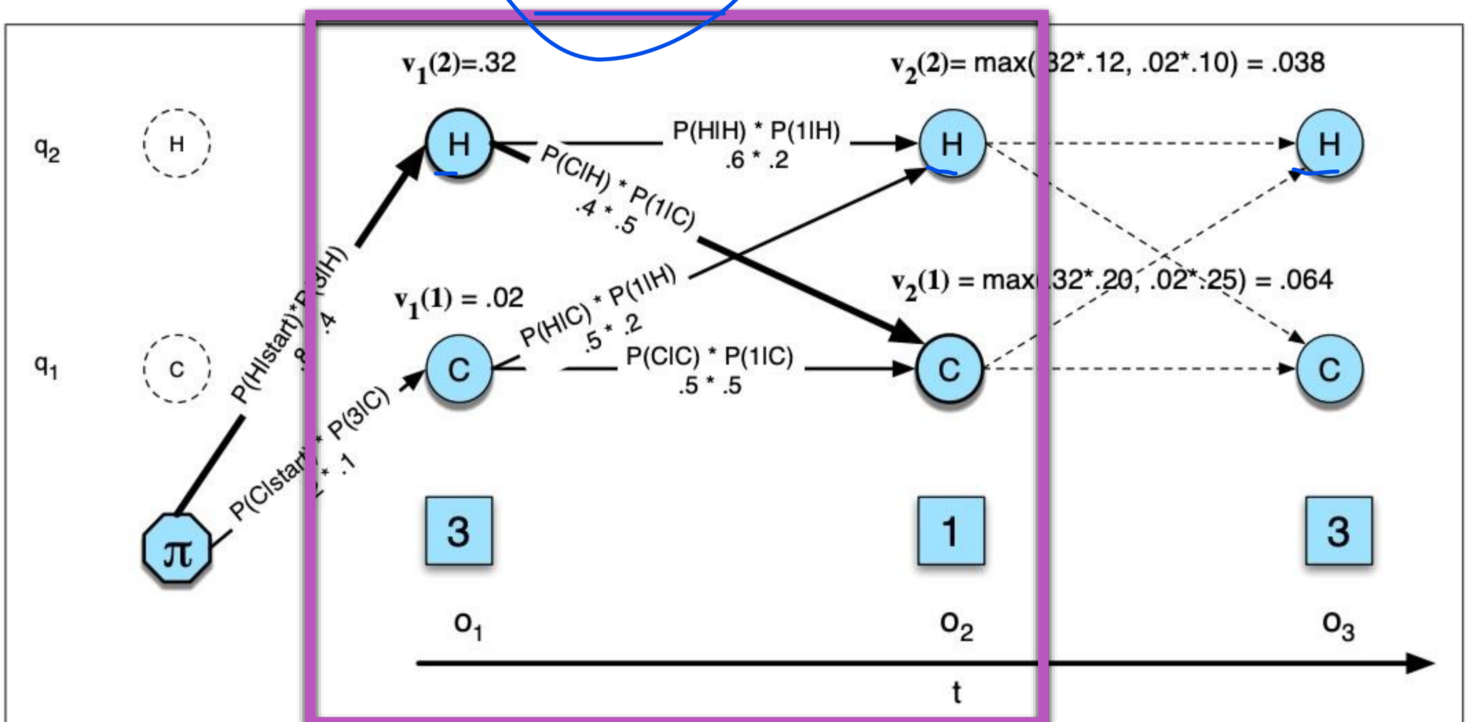
Language Model

- We could enumerate every possible y and calculate the probability? → Too expensive!
- Answer: Impose strong independence assumptions in model, use dynamic programming for globally optimal solutions (e.g. Viterbi algorithm).
- This process is called *decoding*

Viterbi: Decoding with Dynamic Programming

- Impose strong independence assumptions in model:

$$p(x, a|y) = \prod_{j=1}^{l_x} p(x_j | f_{a(j)})$$



Source: "Speech and Language Processing", Chapter A, Jurafsky and Martin, 2019.

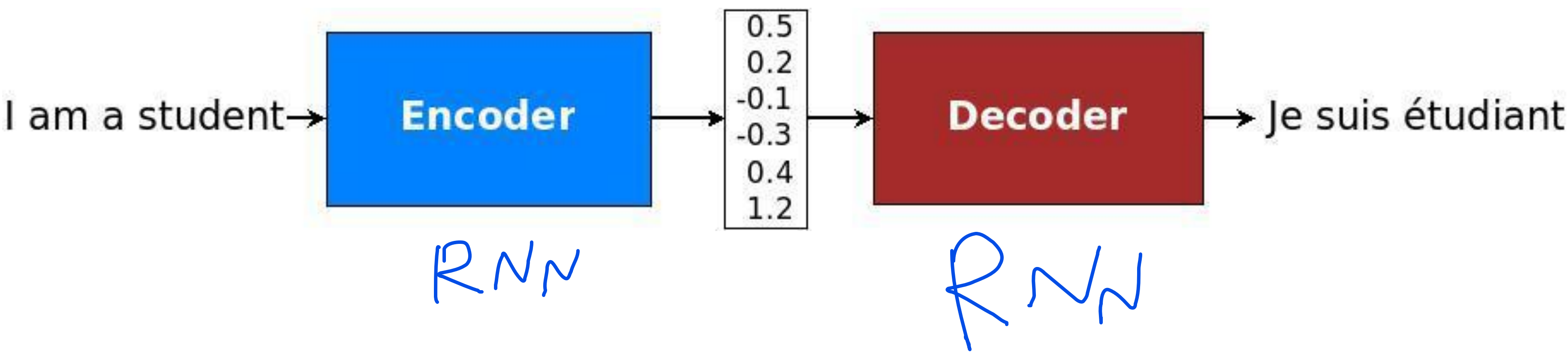
1990s-2010s: Statistical Machine Translation

- SMT was a huge research field
- The best systems were extremely complex
- Hundreds of important details we haven’t mentioned here
- Systems had 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!

Section 2: Neural Machine Translation

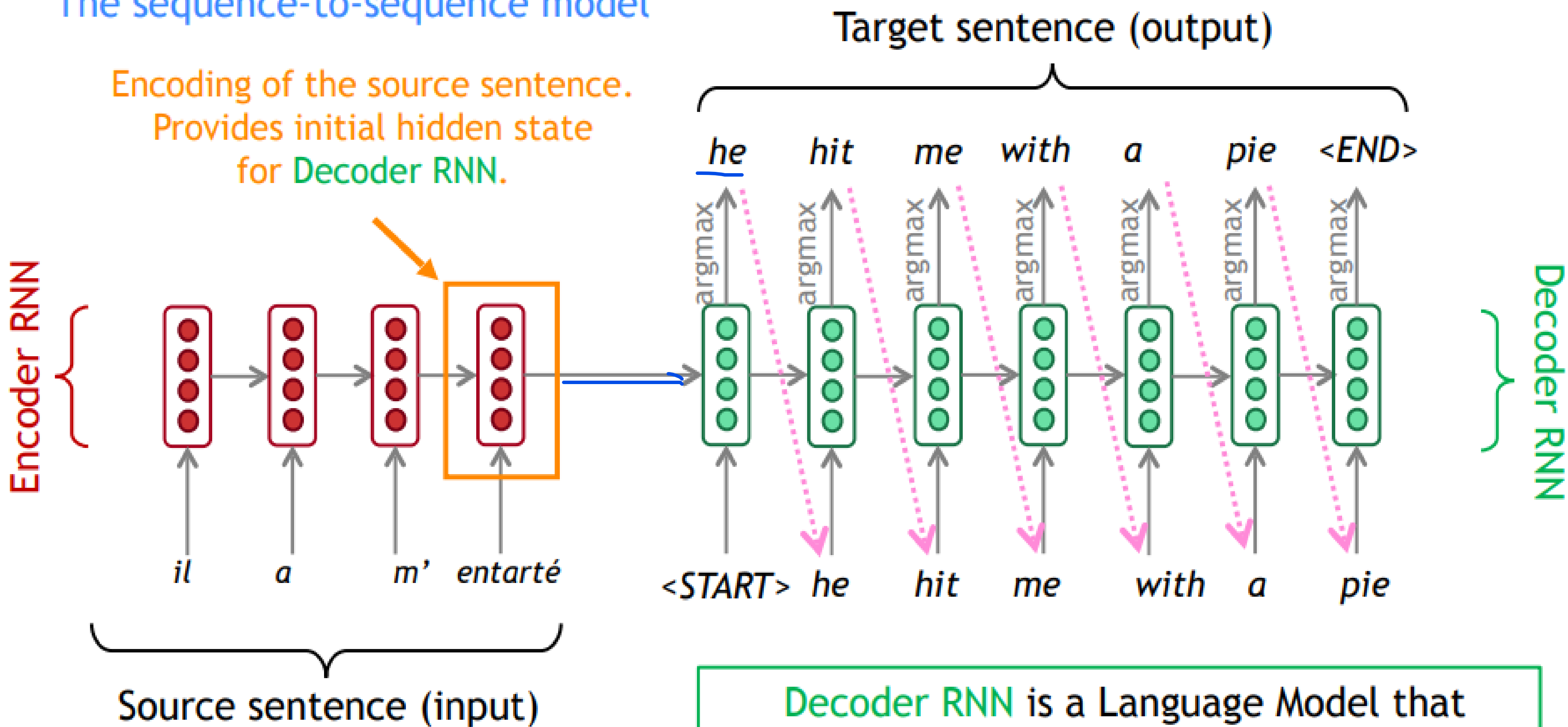
What is Neural Machine Translation?

- 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



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

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)

Neural Machine Translation (NMT)

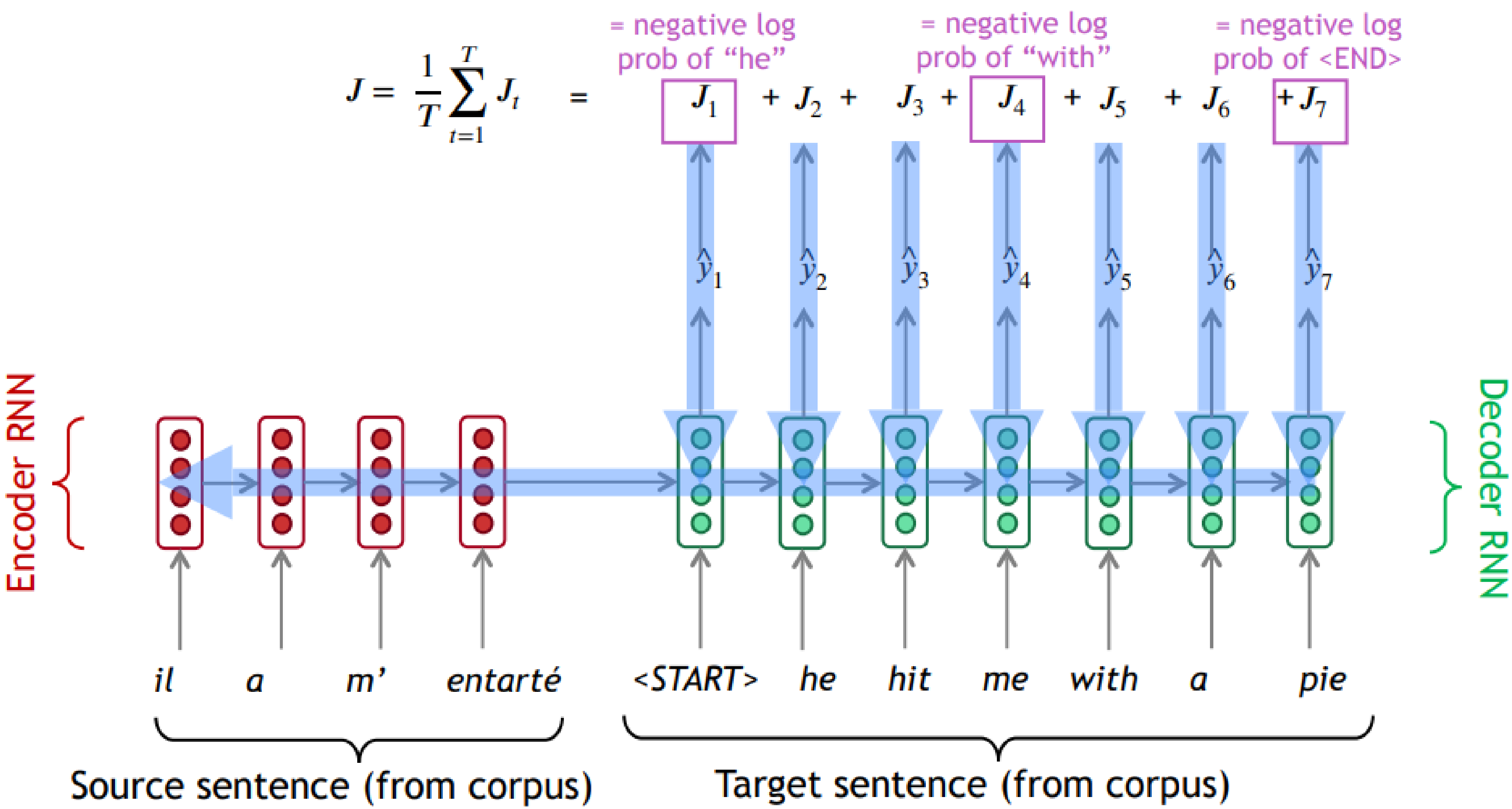
- The sequence-to-sequence model is an example of a **Conditional Language Model**.
  - **Language Model** because the decoder is predicting the next word of the target sentence *y*
  - **Conditional** because its predictions are *also* conditioned on the source sentence *x*

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

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

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

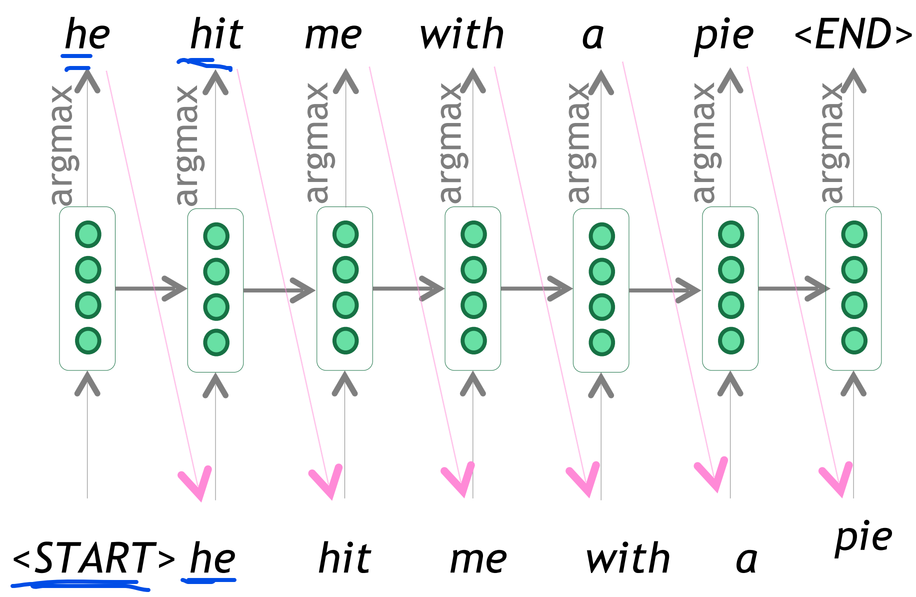
Training a Neural Machine Translation system



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

Greedy decoding

- We saw 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 with this method?**

Problems with greedy decoding

- Greedy decoding has no way to undo decisions!
- Input: *il a m'entarté* *(he hit me with a pie)*
- → *he* _____
- → *he hit* _____
- → *he hit a* _____ (whoops! no going back now…)

- How to fix this?

Exhaustive search decoding

- Ideally, we want to find a (length *T*) translation *y* that maximizes

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

- We could try computing all possible sequences *y*
- This means that on each step *t* of the decoder, we're tracking V^t possible partial translations, where *V* is vocab size
- This $O(V^T)$ complexity is far too expensive!

Beam search decoding

- Core idea: On each step of decoder, keep track of the *k* most probable partial translations (which we call *hypotheses*)
- *k* is the beam size (in practice around 5 to 10)

- A hypothesis $y_1, \ldots, y_t$ has a score which is its log probability:

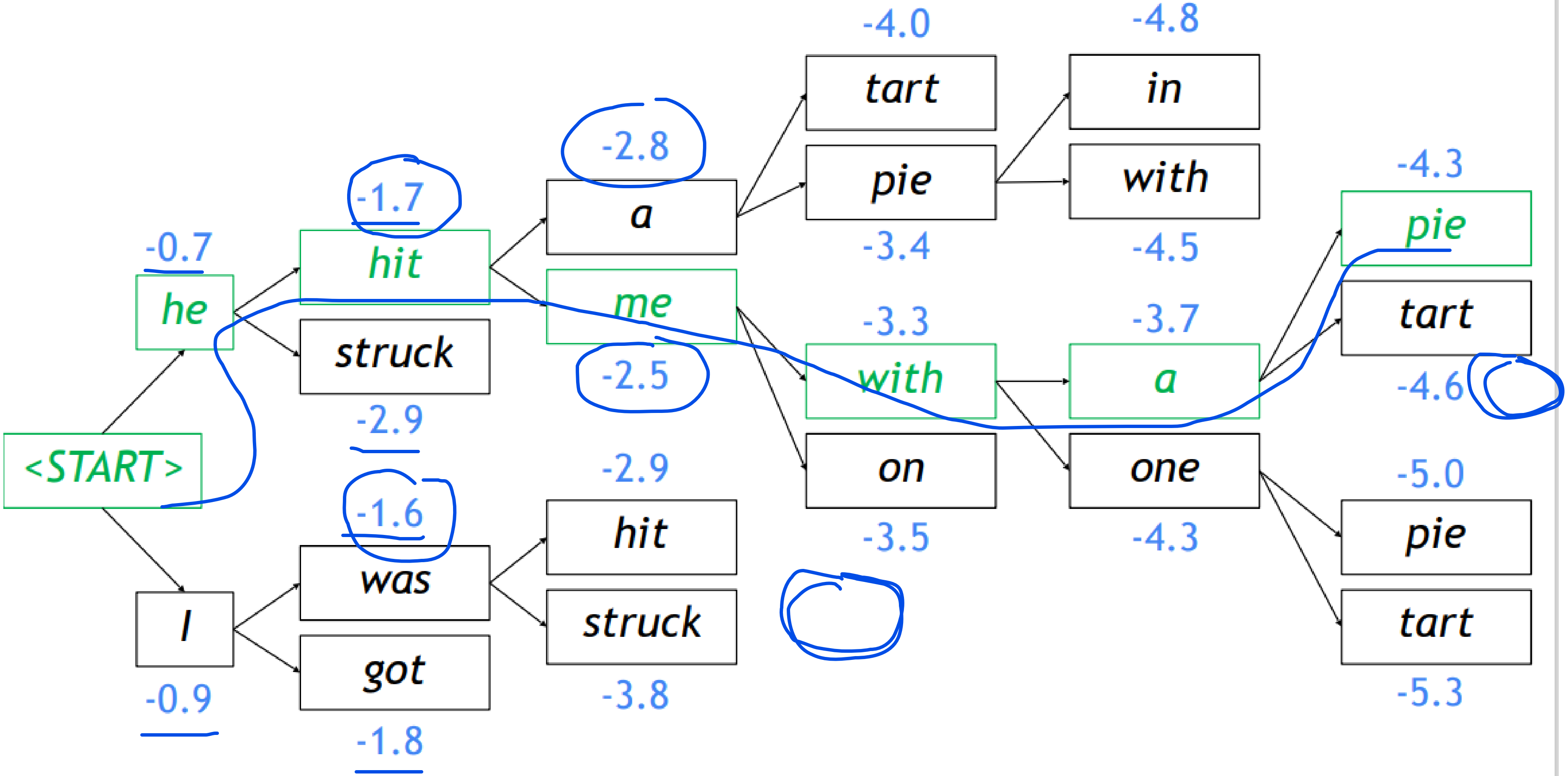
$$\text{score}(y_1, \ldots, y_t) = \log P_{\text{LM}}(y_1, \ldots, y_t|x) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i|y_1, \ldots, y_{i-1}, x)$$

- $\boxed{\text{Scores are all negative, and higher score is better}}$
- We search for high-scoring hypotheses, tracking top *k* on each step

- Beam search is not guaranteed to find optimal solution
- But much more efficient than exhaustive search!

Beam search decoding: example

Beam size = k = 2. Blue numbers = $\text{score}(y_1, \ldots, y_t) = \sum_{i=1}^{t} \log P_{\text{LM}}(y_i | y_1, \ldots, y_{i-1}, x)$



Backtrack to obtain the full hypothesis

Beam search decoding: stopping criterion

- In greedy decoding, usually we decode until the model produces a <END> token
  - For example: *<START> he hit me with a pie <END>*

- In beam search decoding, different hypotheses may produce <END> tokens on different timesteps
  - When a hypothesis produces <END>, that hypothesis is complete.
  - Place it aside and continue exploring other hypotheses via beam search.

- Usually we continue beam search until:
  - We reach timestep T (where T is some pre-defined cutoff), or
  - We have at least n completed hypotheses (where n is pre-defined cutoff)

Beam search decoding: finishing up

- 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

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

- Problem with this: longer hypotheses have lower scores

- Fix: 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 (**B**ilingual **E**valuation **U**nderstudy)

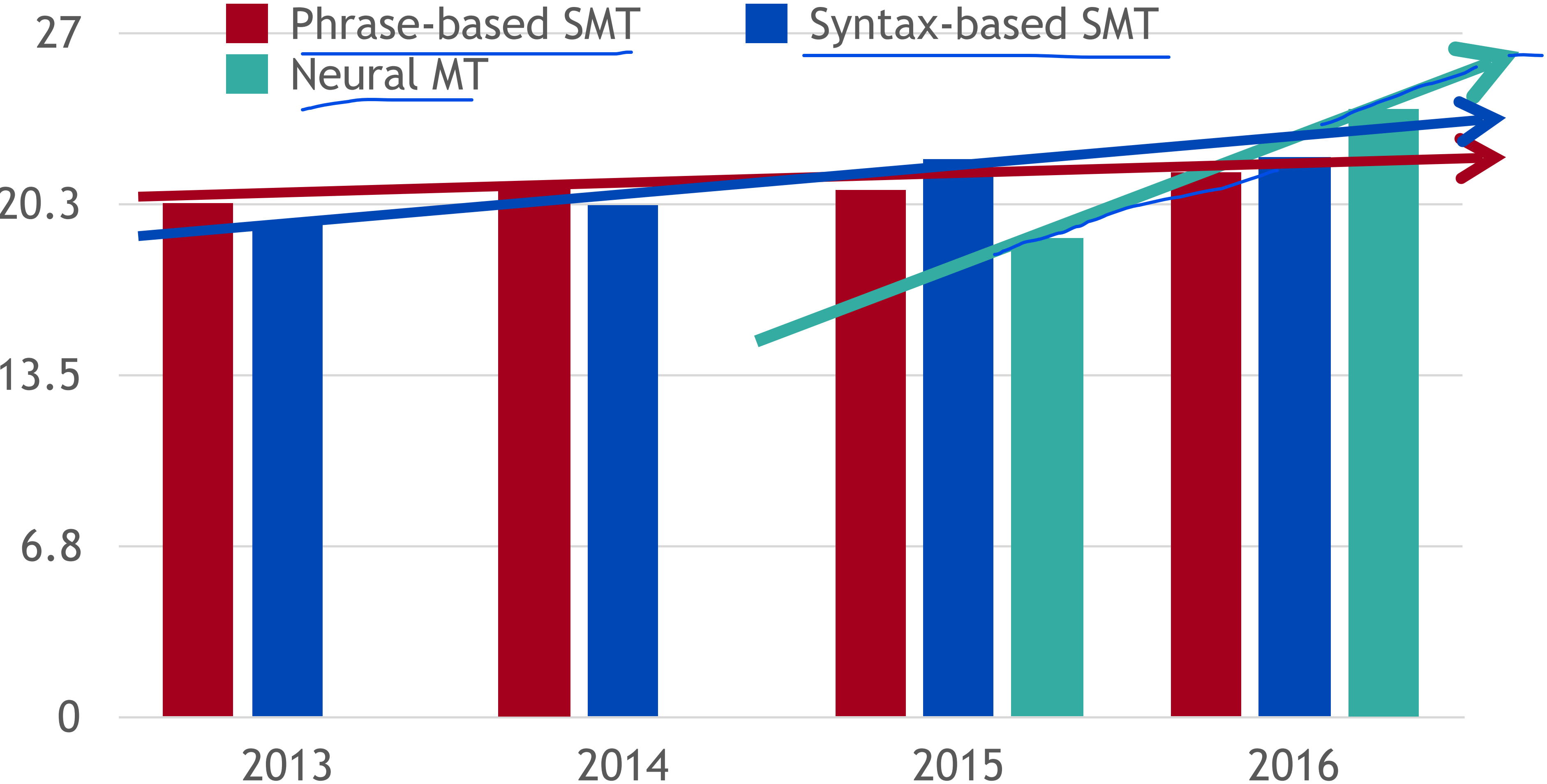
- BLEU compares the machine-written translation to one or several human-written translation(s), and computes a similarity score based on:
  - *n*-gram precision (usually for 1, 2, 3 and 4-grams)
  - Plus a penalty for too-short system translations

- 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 ☹

Source: "BLEU: a Method for Automatic Evaluation of Machine Translation", Papineni et al, 2002. http://aclweb.org/anthology/P02-1040

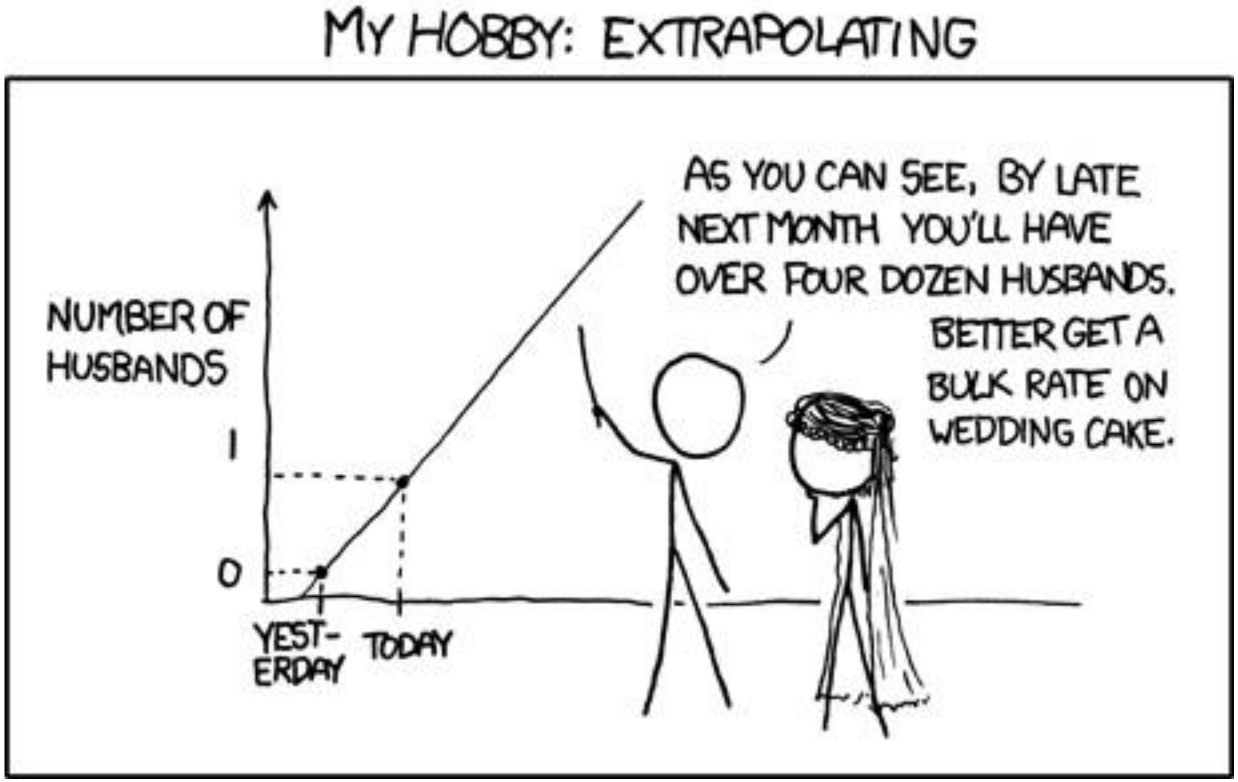
MT progress over time

[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

MT progress over time



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

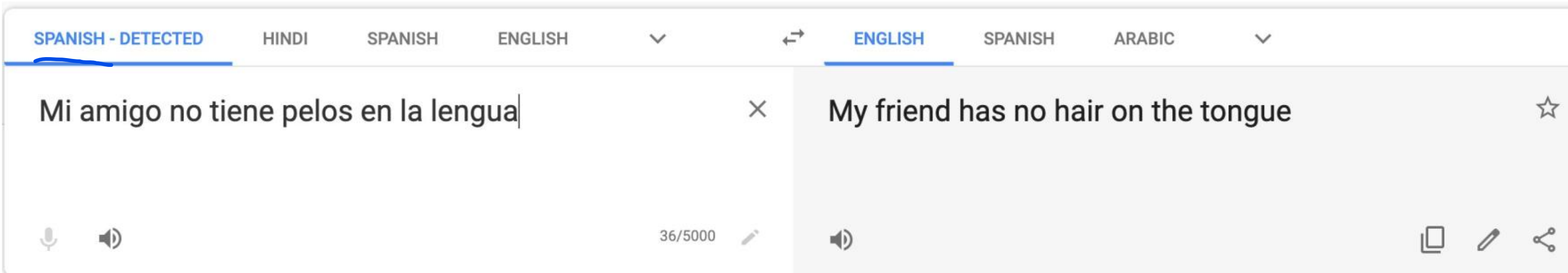
So is Machine Translation solved?

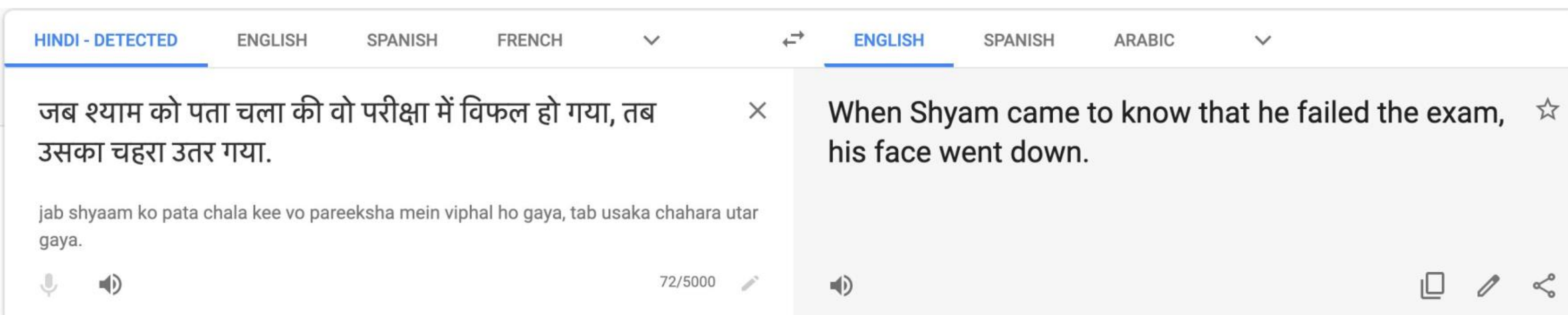
- **Nope!**
- Many difficulties remain:
  - o Out-of-vocabulary words
  - o Domain mismatch between train and test data
  - o Maintaining context over longer text
  - o Low-resource language pairs

Further reading: *"Has AI surpassed humans at translation? Not even close!"*
https://www.skynettoday.com/editorials/state_of_nmt

So is Machine Translation solved?

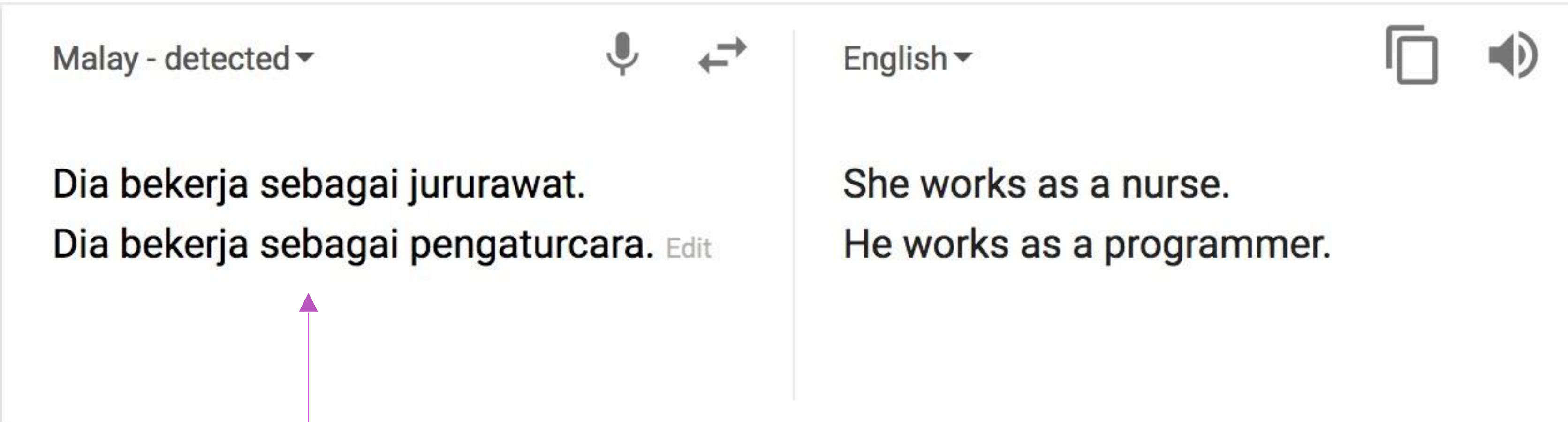
- Nope!
- Using common sense is still hard
- Idioms are difficult to translate





So is Machine Translation solved?

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

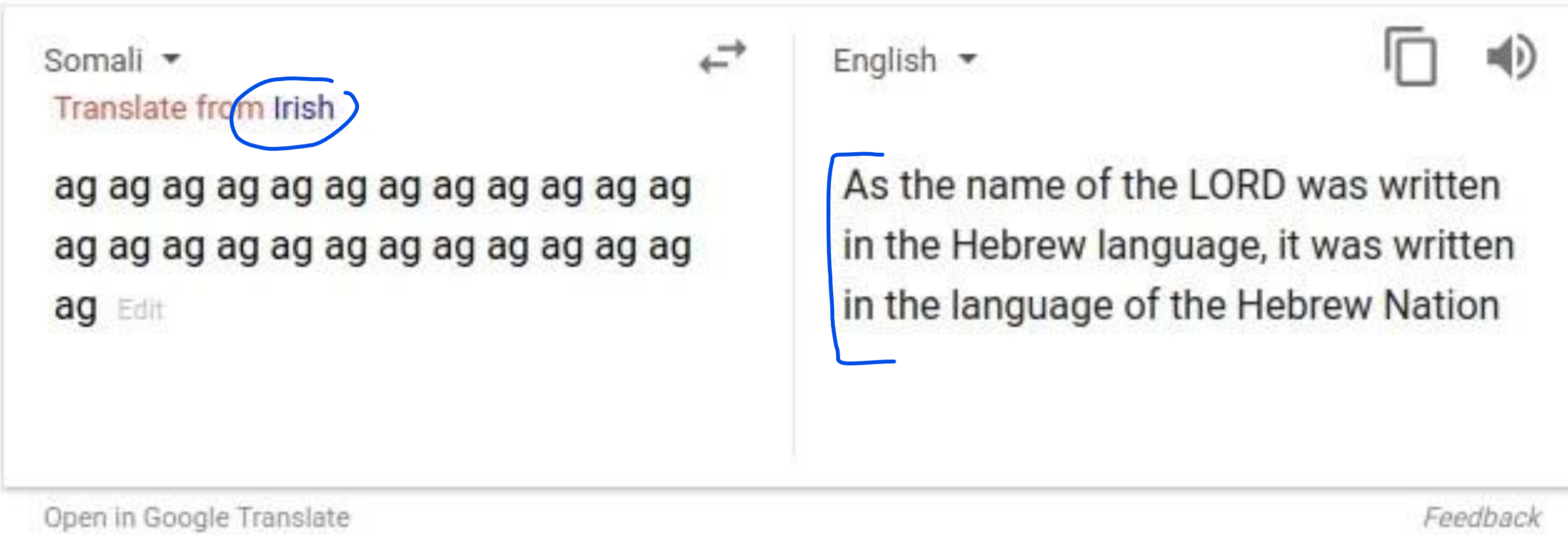


Didn’t specify gender

Source: https://hackernoon.com/bias-sexist-or-this-is-the-way-it-should-bece1f7c8c683c

So is Machine Translation solved?

- Nope!
- Uninterpretable systems do strange things



Picture source: https://www.vice.com/en_uk/article/j5npeg/why-is-google-translate-spitting-out-sinisterreligious-prophecies
Explanation: https://www.skynettoday.com/briefs/google-nmt-prophecies

NMT research continues

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

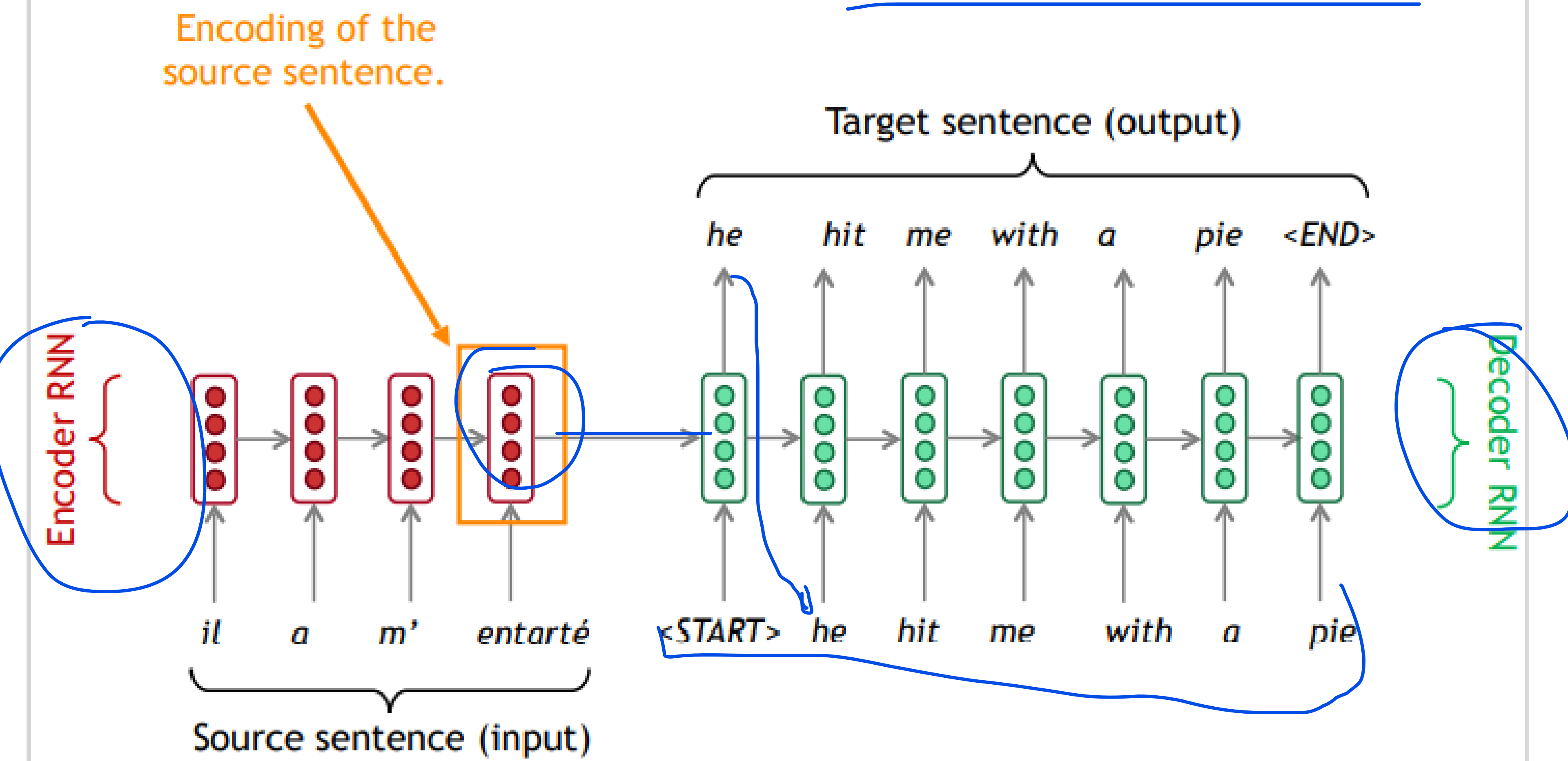
- NMT research has pioneered many of the recent innovations of NLP Deep Learning

- In **2019**: 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

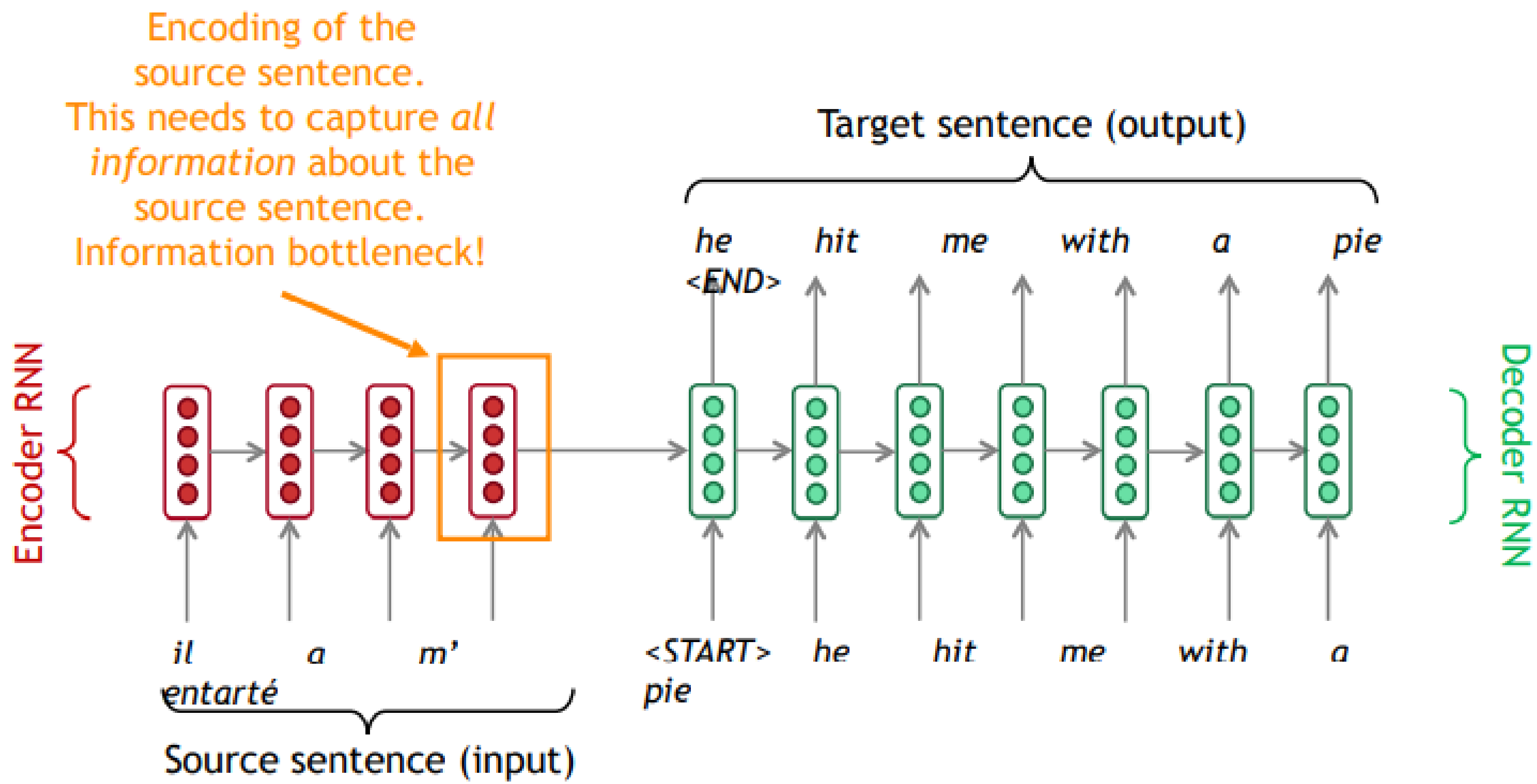
Section 3: Attention

Sequence-to-sequence: the bottleneck problem



Problems with this architecture?

Sequence-to-sequence: the bottleneck problem



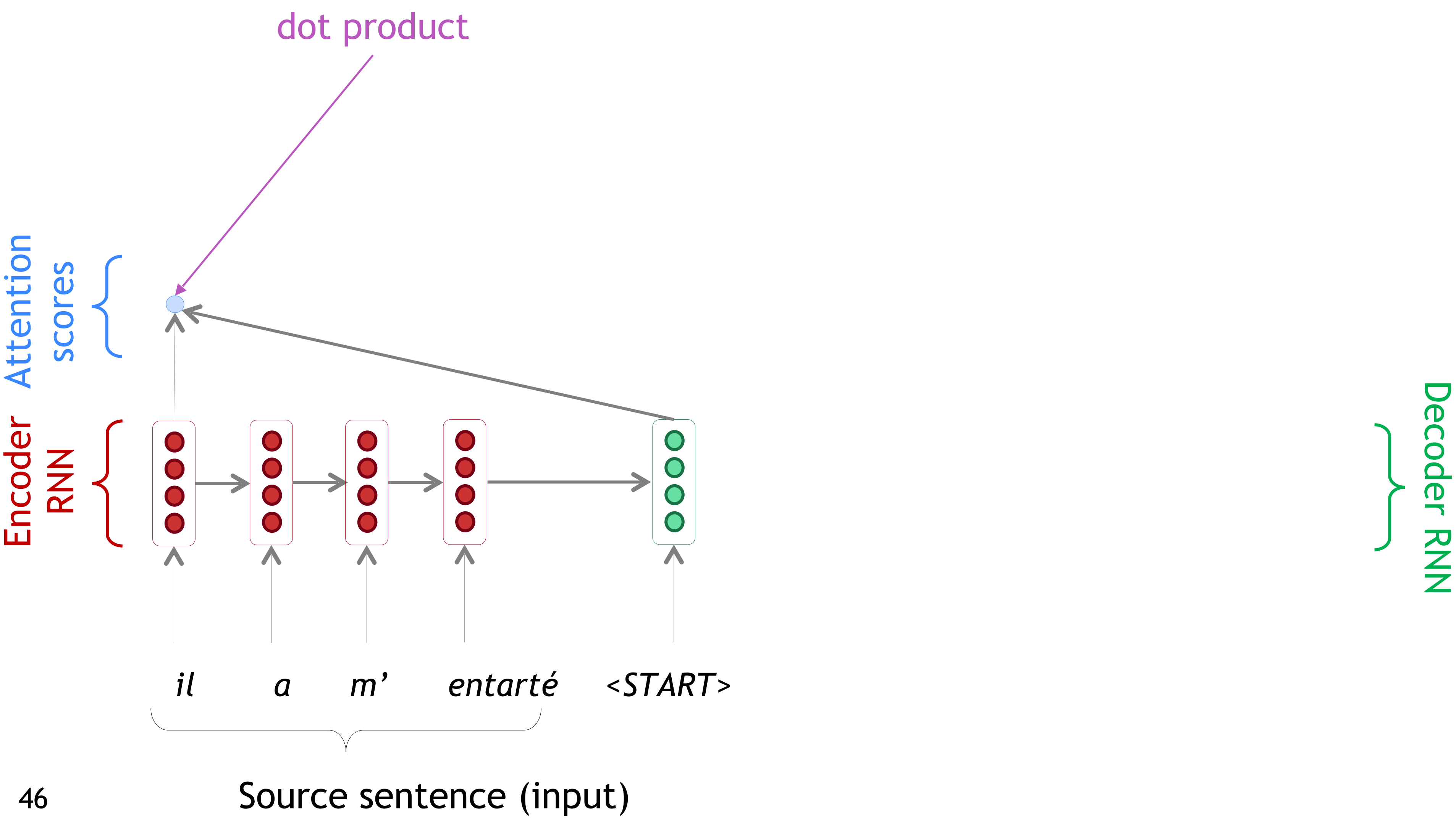
Attention

- Attention provides a solution to the bottleneck problem.

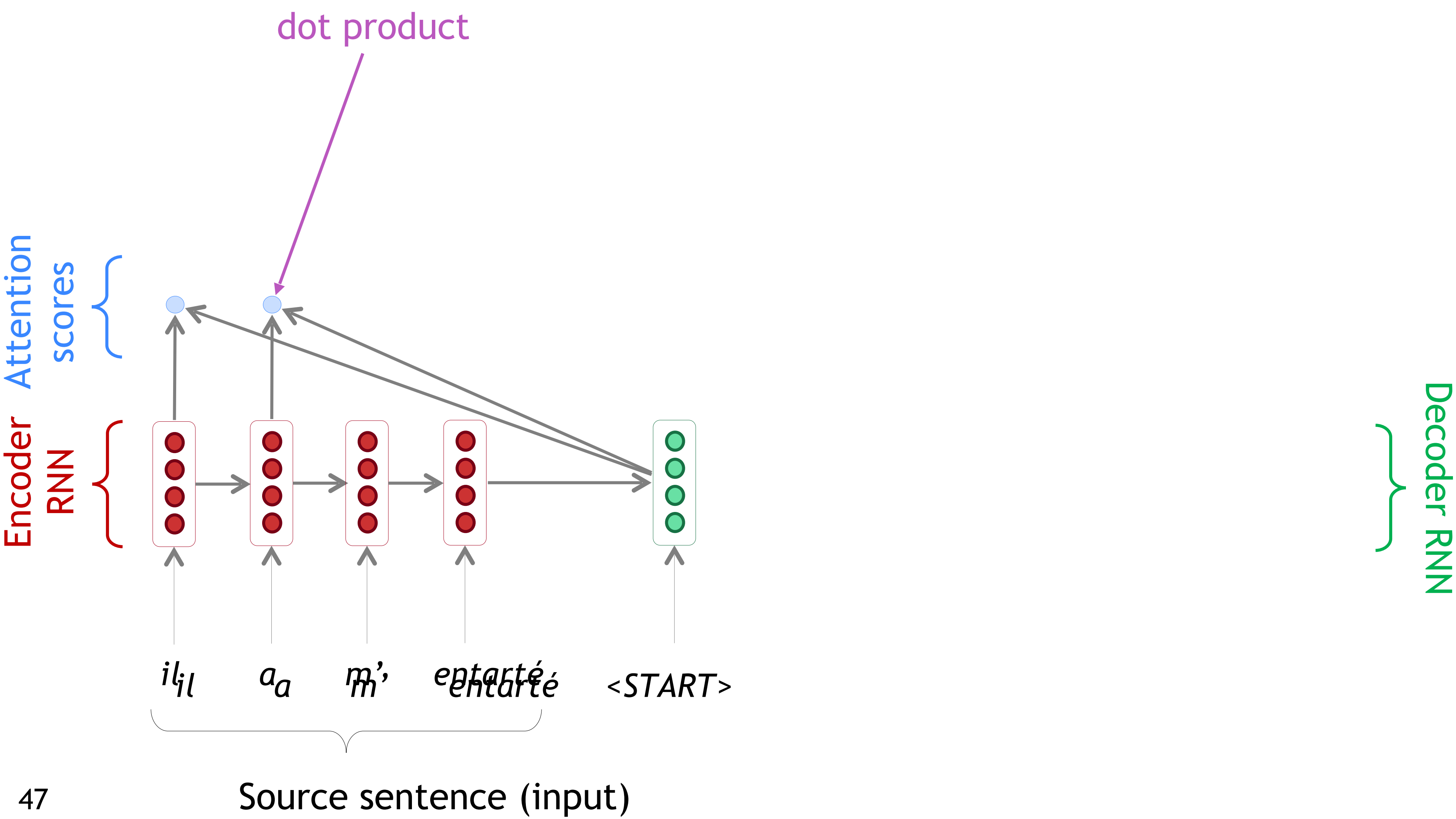
- Core idea: on each step of the decoder, use *direct connection to the encoder* to *focus on a particular part* of the source sequence

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

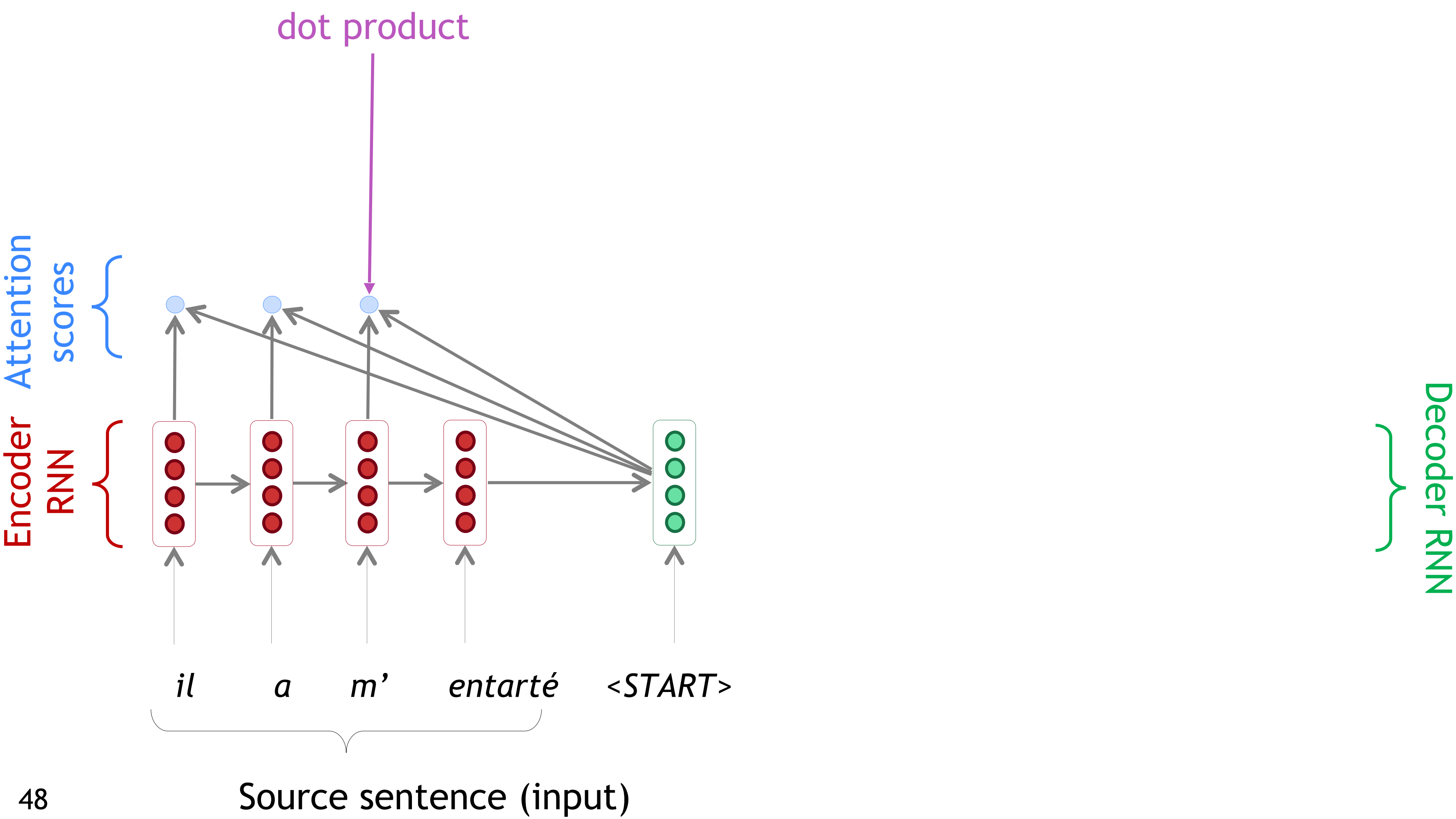
Sequence-to-sequence with attention

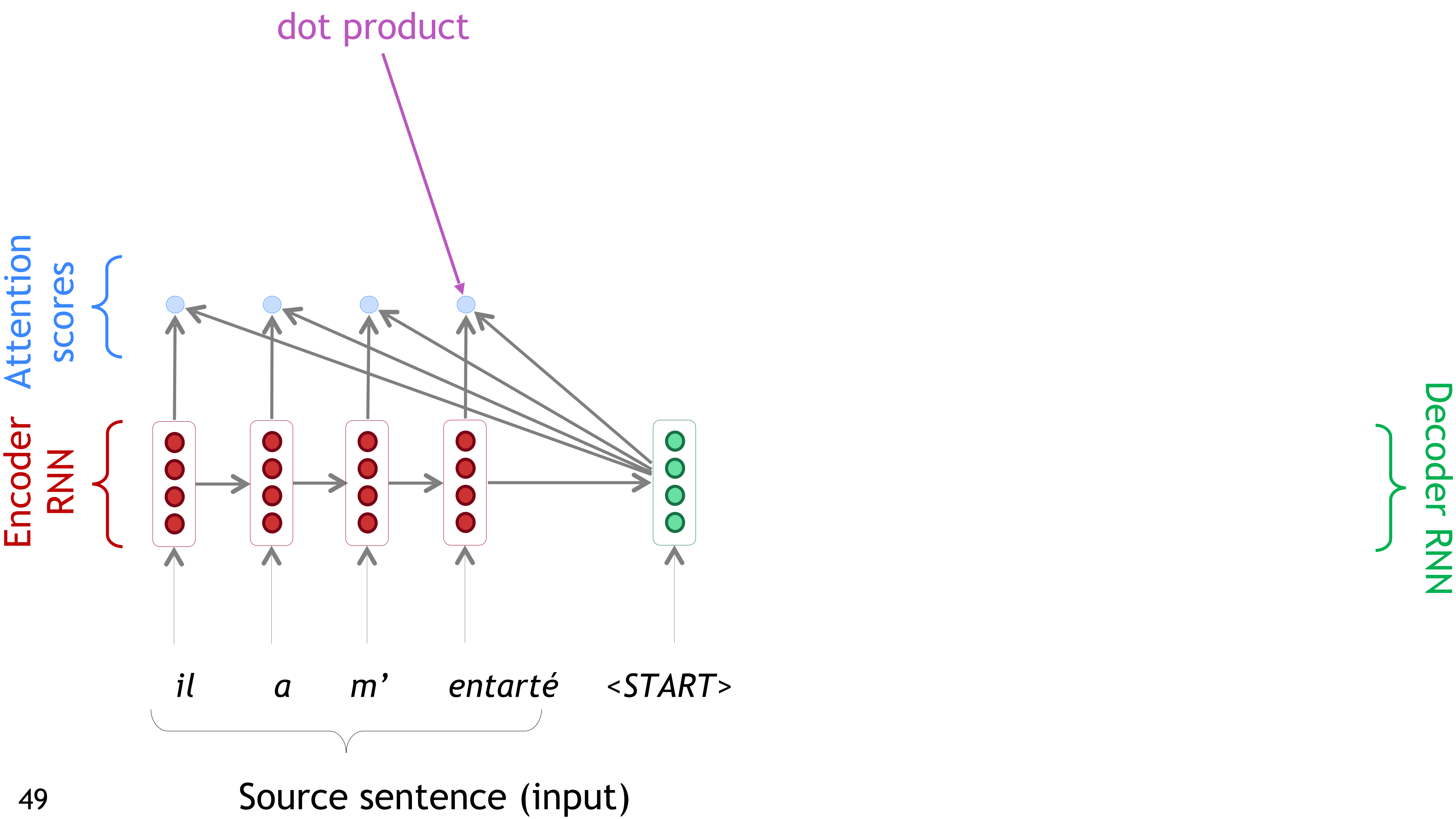


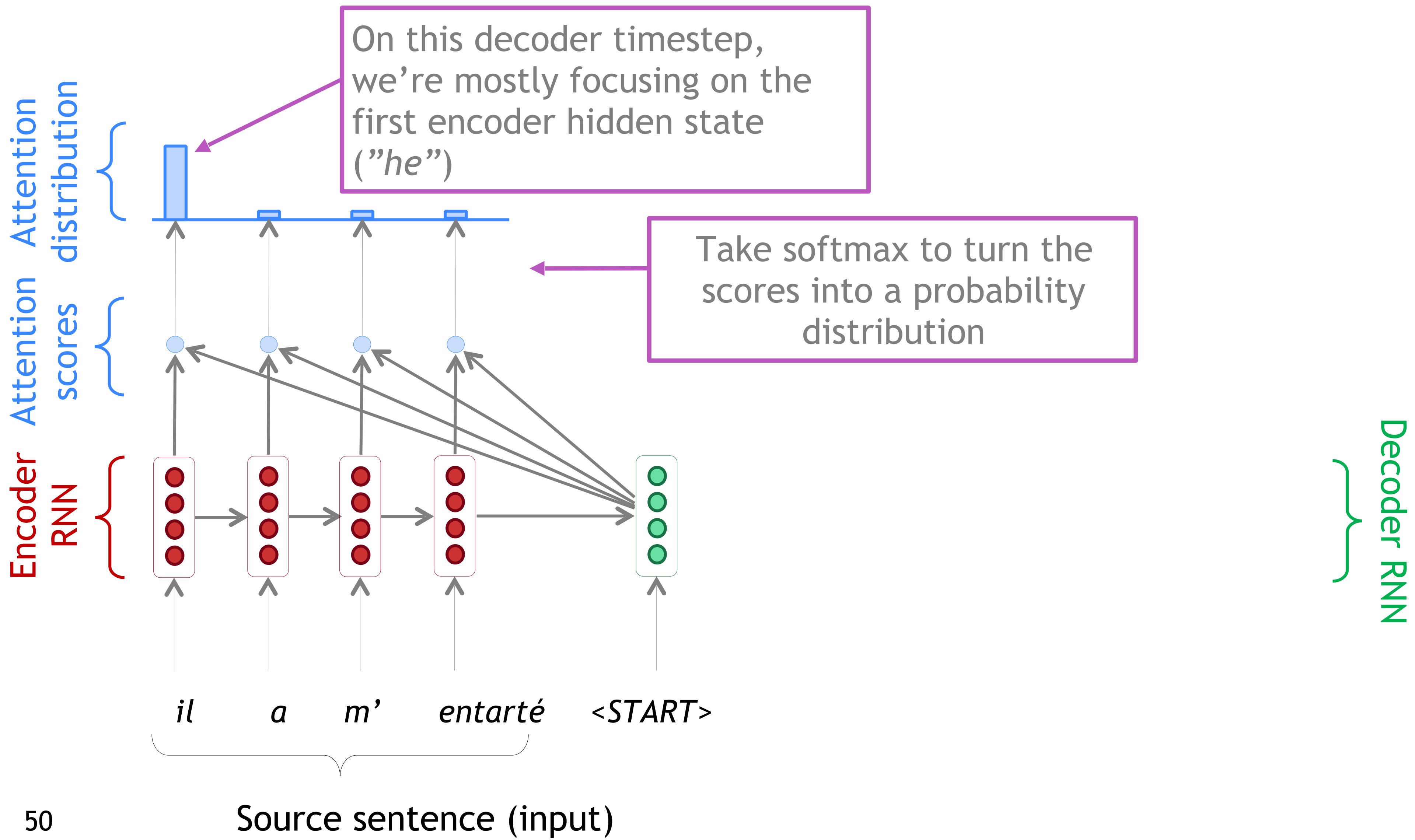
Sequence-to-sequence with attention



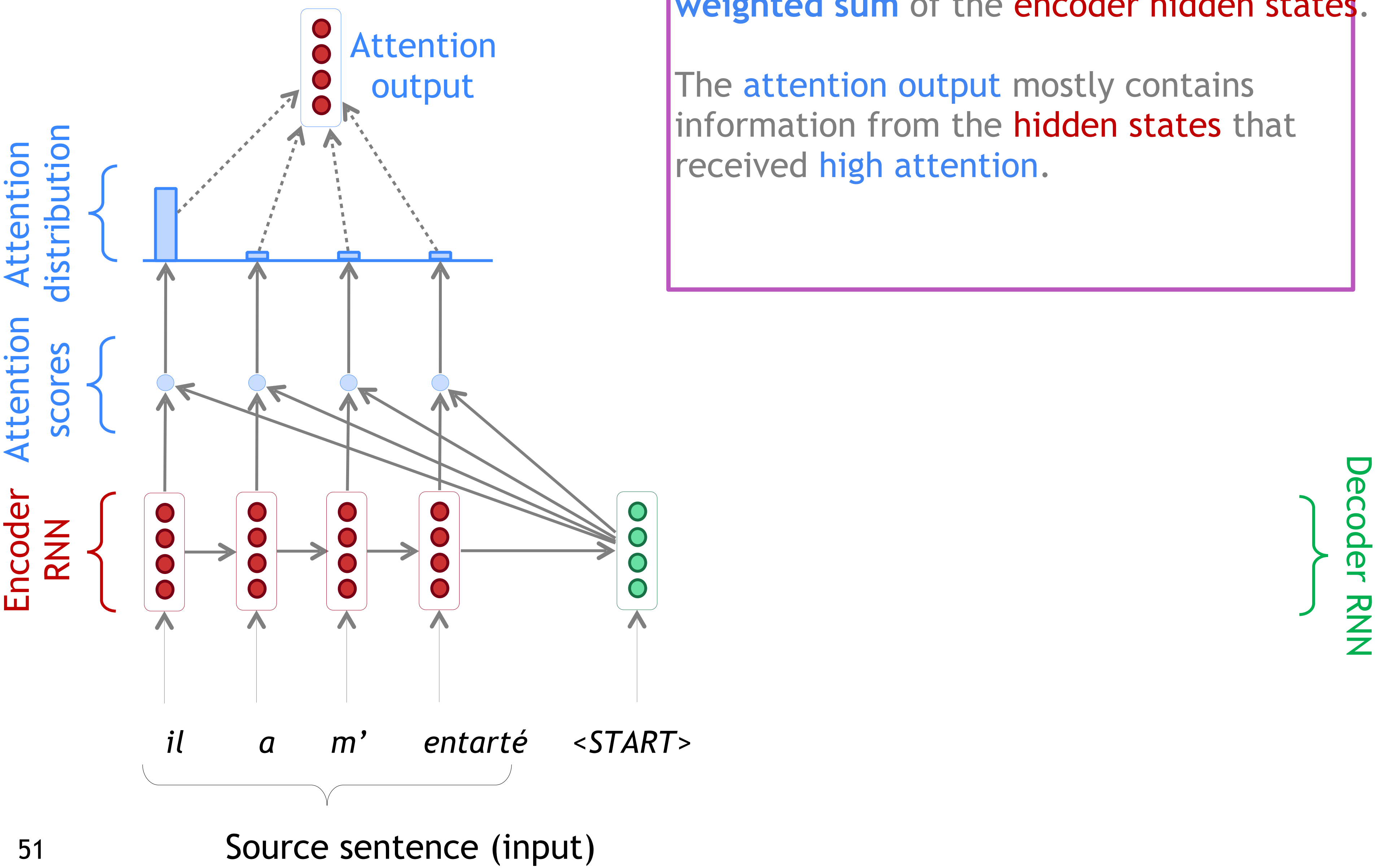
Sequence-to-sequence with attention




dot product
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
Source sentence (input)

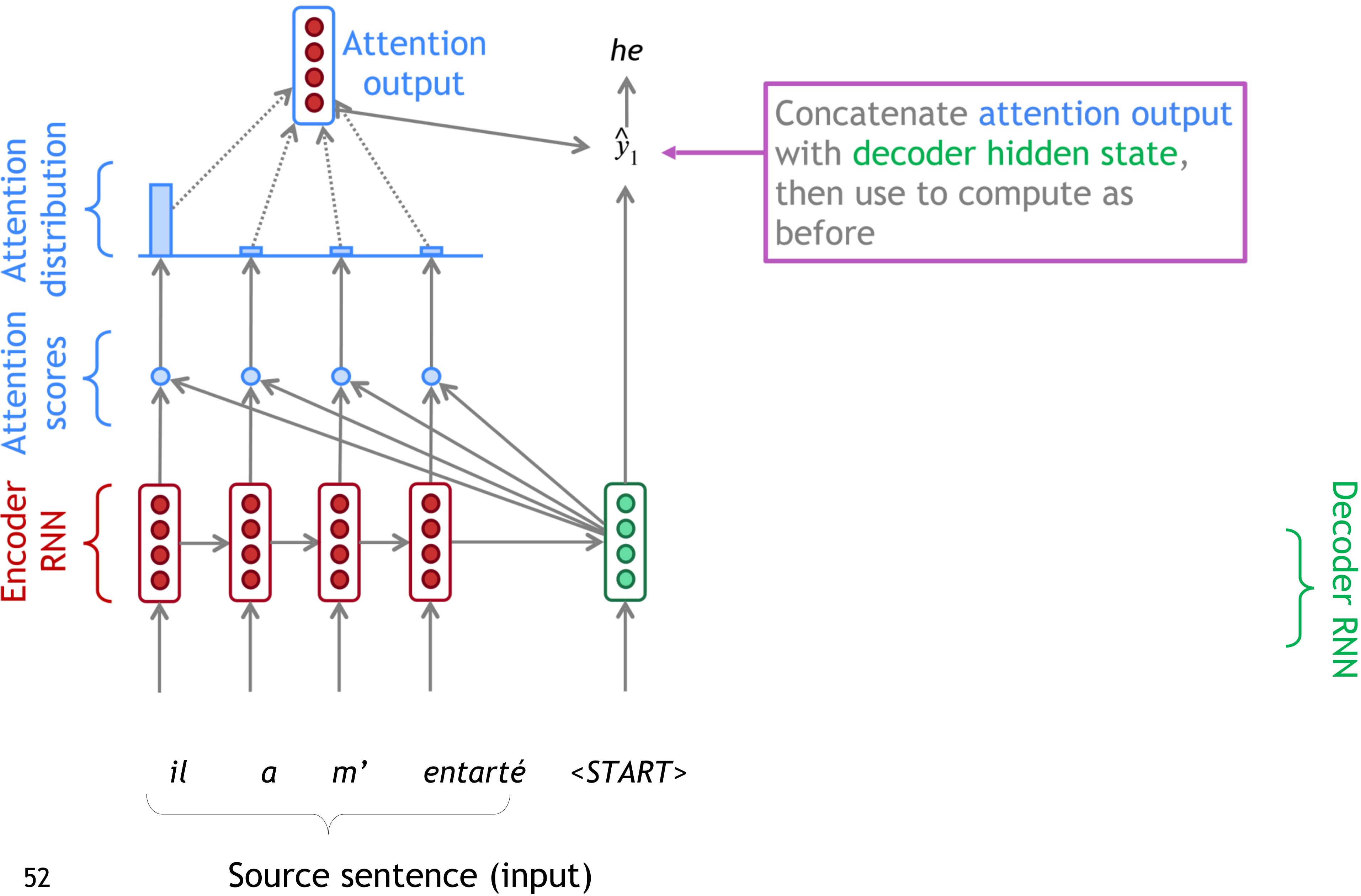


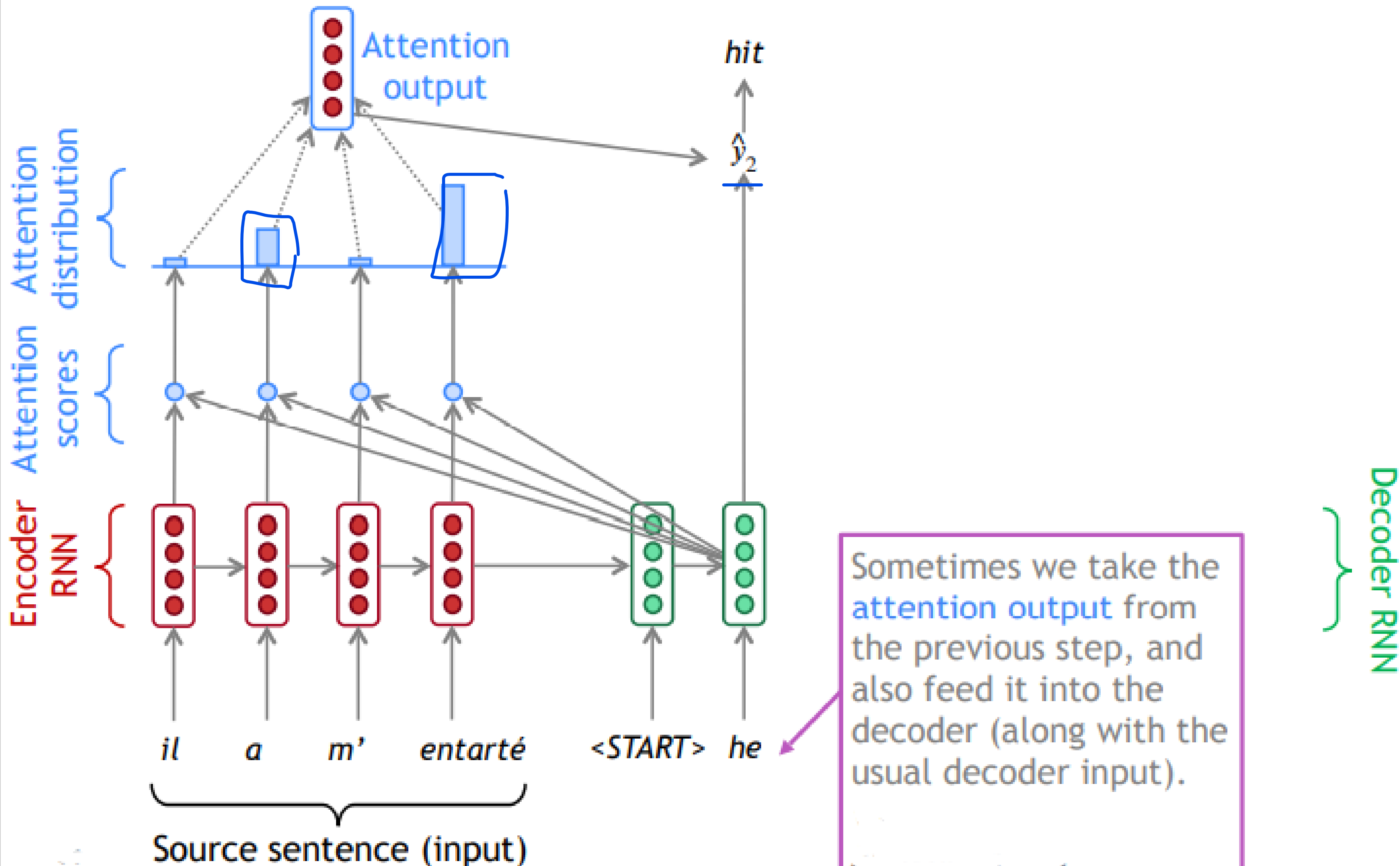
On this decoder timestep, we're mostly focusing on the first encoder hidden state (*"he"*)
Take softmax to turn the scores into a probability distribution
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
Source sentence (input)



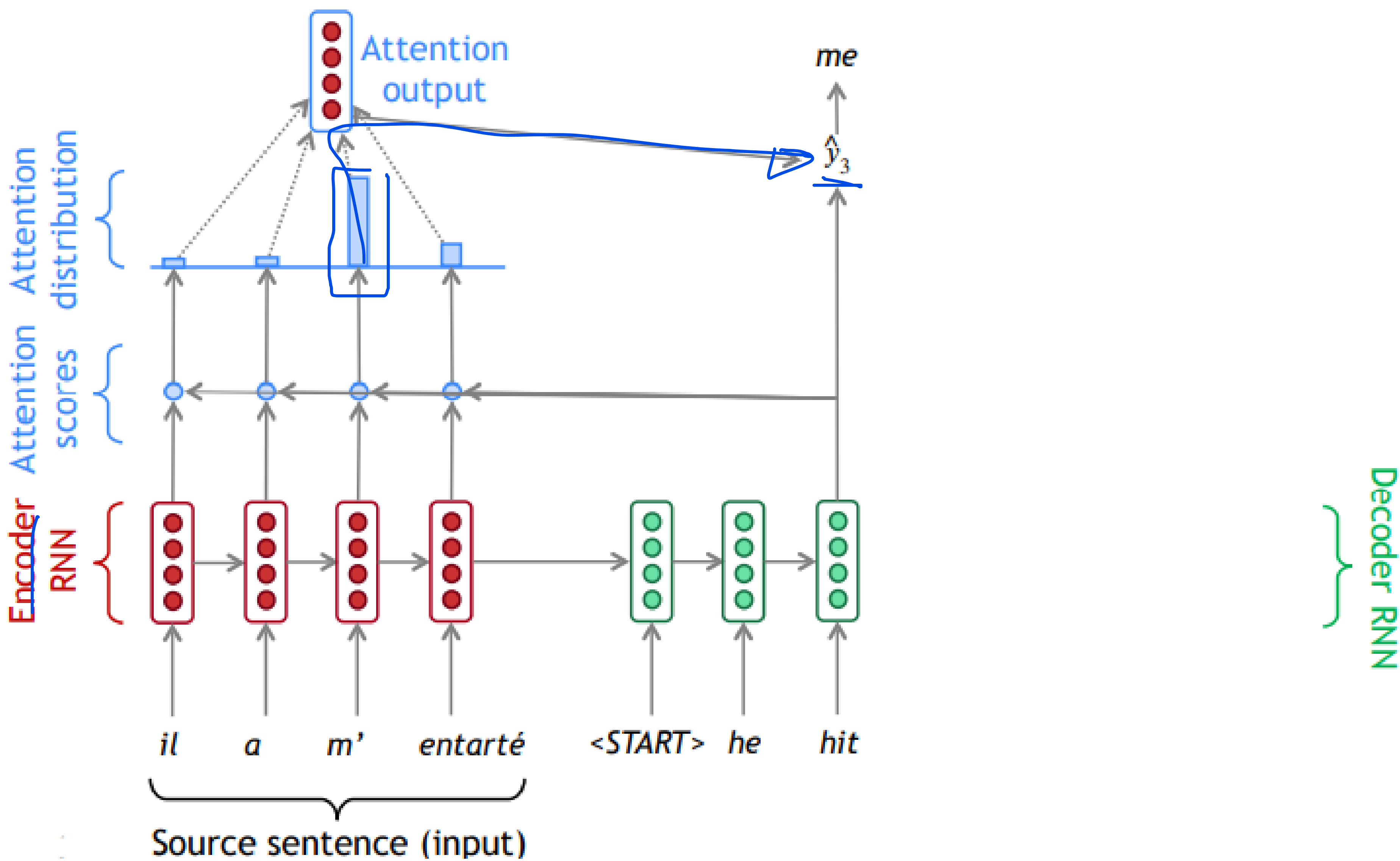
Use the attention distribution to take a **weighted sum** of the encoder hidden states.

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

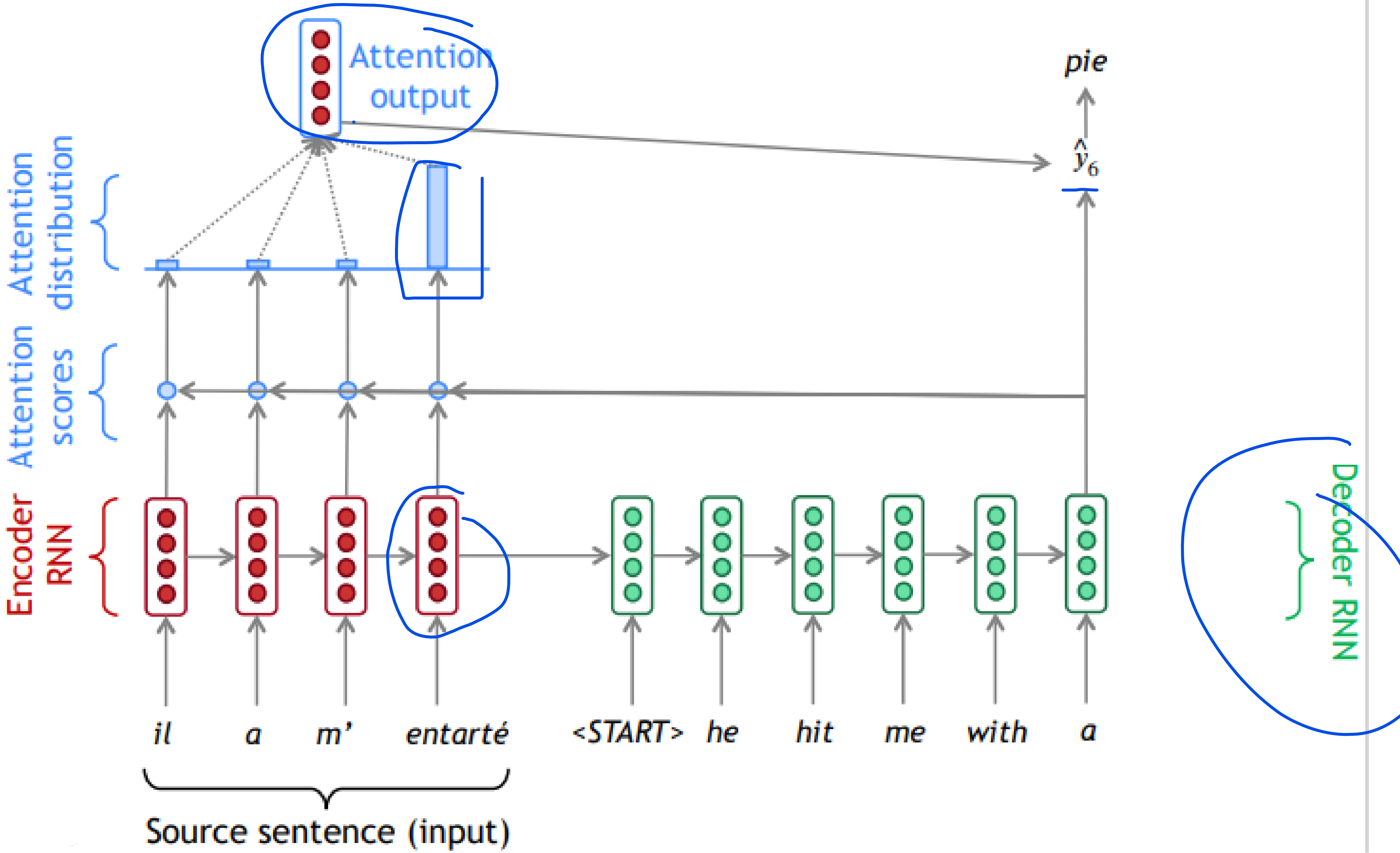

Attention output
he
$\hat{y}_1$
Concatenate attention output with decoder hidden state, then use to compute as before
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m’
entarté
<START>
Source sentence (input)



Sometimes we take the attention output from the previous step, and also feed it into the decoder (along with the usual decoder input).


Attention output
me
$\hat{y}_3$
Attention distribution
Attention scores
Encoder RNN
Decoder RNN
il
a
m'
entarté
<START>
he
hit
Source sentence (input)

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

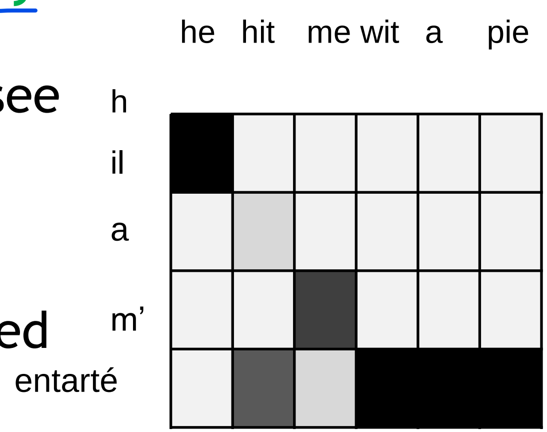
$$\boldsymbol{a}_t = \sum_{i=1}^{N} \alpha_i^t \boldsymbol{h}_i \in \mathbb{R}^h$$

- 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 (soft) alignment for free!
  - This is cool because we never explicitly trained an alignment system



- The network just learned alignment by itself

Attention is a *general* Deep Learning technique

- We've seen that attention is a great way to improve the sequence-to-sequence model for Machine Translation.
- <u>However</u>: You can use attention in many architectures (not just seq2seq) and many tasks (not just MT)

- <u>**More general definition of attention**</u>:
    - Given a set of vector *values*, and a vector *query*, <u>**attention**</u> is a technique to compute a weighted sum of the values, dependent on the query.

- We sometimes say that the query *attends to* the values.
- For example, in the seq2seq + attention model, each decoder hidden state (query) *attends to* all the encoder hidden states (values).

Attention is a *general* Deep Learning technique

More general definition of attention:

Given a set of vector *values*, and a vector *query*, **attention** is a technique to compute a weighted sum of the values, dependent on the query.

Intuition:

- The weighted sum is a *selective summary* of the information contained in the values, where the query determines which values to focus on.
- Attention is a way to obtain a *fixed-size representation of an arbitrary set of representations* (the values), dependent on some other representation (the query).

There are *several* attention variants

- We have some *values* $\boldsymbol{h}_1, \ldots, \boldsymbol{h}_N \in \mathbb{R}^{d_1}$ and a $\boldsymbol{s} \in \mathbb{R}^{d_2}$

- Attention always involves:
  1. Computing the *attention scores* $\boldsymbol{e} \in \mathbb{R}^N$
  2. Taking softmax to get *attention distribution* α:

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

  3. Using attention distribution to take weighted sum of values:

$$\boldsymbol{a} = \sum_{i=1}^{N} \alpha_i \boldsymbol{h}_i \in \mathbb{R}^{d_1}$$

thus obtaining the *attention output* ***a*** (sometimes called the *context vector*)

There are multiple ways to do this

Attention variants

There are several ways you can comp $e \in \mathbb{R}^N$ $h_1, \ldots, h_N \in \mathbb{R}^{d_1}$
and $s \in \mathbb{R}^{d_2}$:

- Basic dot-product $e_i = s^T h_i \in \mathbb{R}$ attention:
- Note: this $d_1 = d_2$ assumes
- This is the version we saw earlier

- Multiplicative attention: $e_i = s^T W h_i \in \mathbb{R}$
- Where $W \in \mathbb{R}^{d_2 \times d_1}$ is a weight matrix

- Additive attention: $e_i = v^T \tanh(W_1 h_i + W_2 s) \in \mathbb{R}$
- Where $W_1 \in \mathbb{R}^{d_3 \times d_1}, W_2 \in \mathbb{R}^{d_3 \times d_2}$ are weight matrice $v \in \mathbb{R}^{d_3}$ is a weight vector.
- d_3 (the attention dimensionality) is a hyperparameter

More information:

"Deep Learning for NLP Best Practices", Ruder, 2017. http://ruder.io/deep-learning-nlp-best-practices/ index.html#attention
"Massive Exploration of Neural Machine Translation Architectures", Britz et al, 2017, https://arxiv.org/pdf/

Summary

- We learned some 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!