

Section 2: Neural Machine Translation

CS224N/Ling284

2014

(dramatic reenactment)

2014

Neural
Machine
Translation

MT research

(dramatic reenactment)

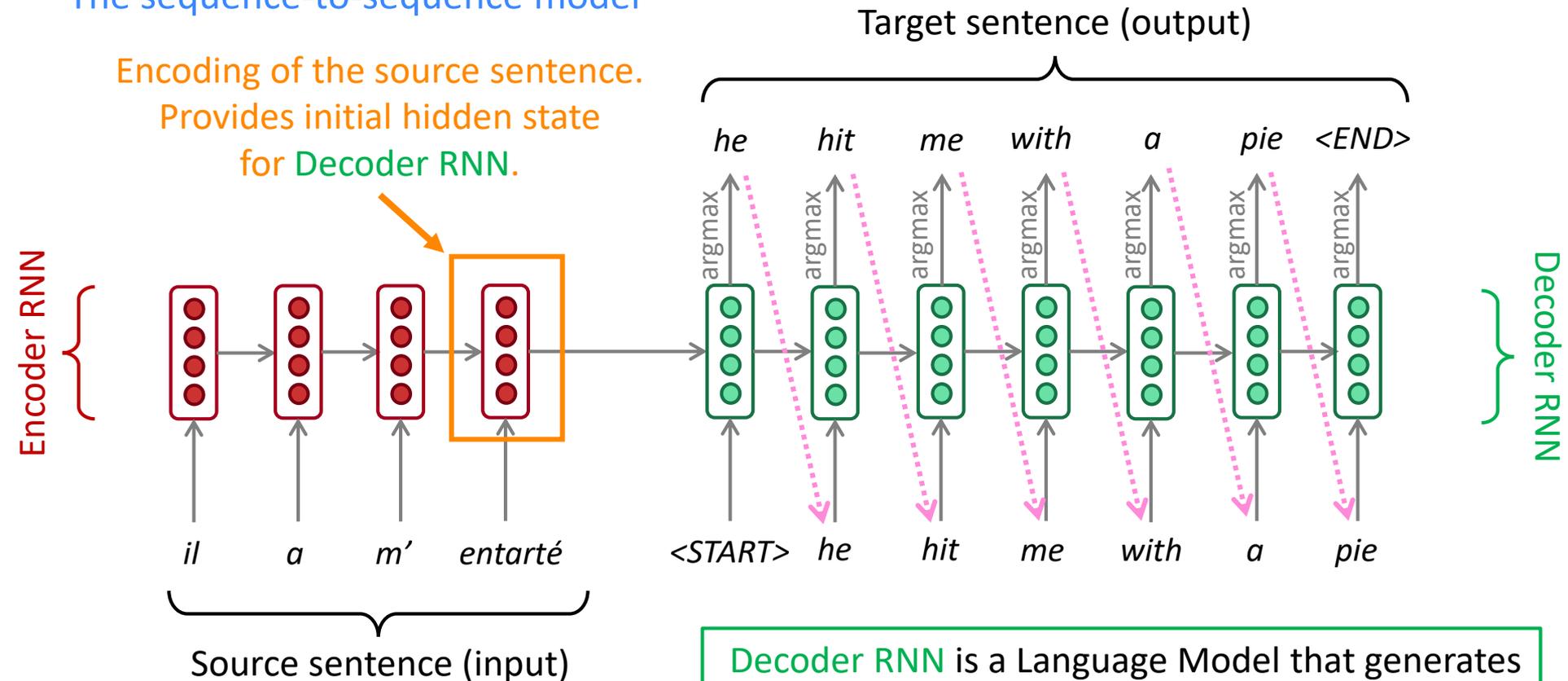
What is Neural Machine Translation?

- 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

Encoding of the source sentence.
Provides initial hidden state
for Decoder RNN.



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 $P(y|x)$:

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

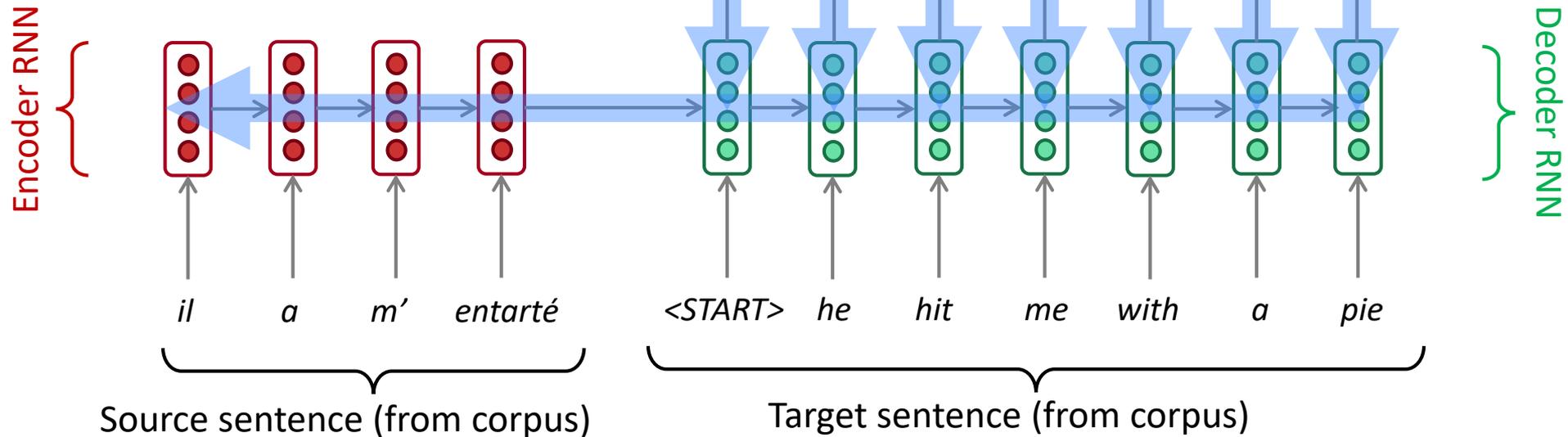
Probability of next target word, given target words so far and source sentence x

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

Training a Neural Machine Translation system

$$J = \frac{1}{T} \sum_{t=1}^T J_t = J_1 + J_2 + J_3 + J_4 + J_5 + J_6 + J_7$$

= negative log prob of "he" = negative log prob of "with" = negative log prob of <END>



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

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

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

- 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, \dots, y_t has a *score* which is its log probability:

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

- 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

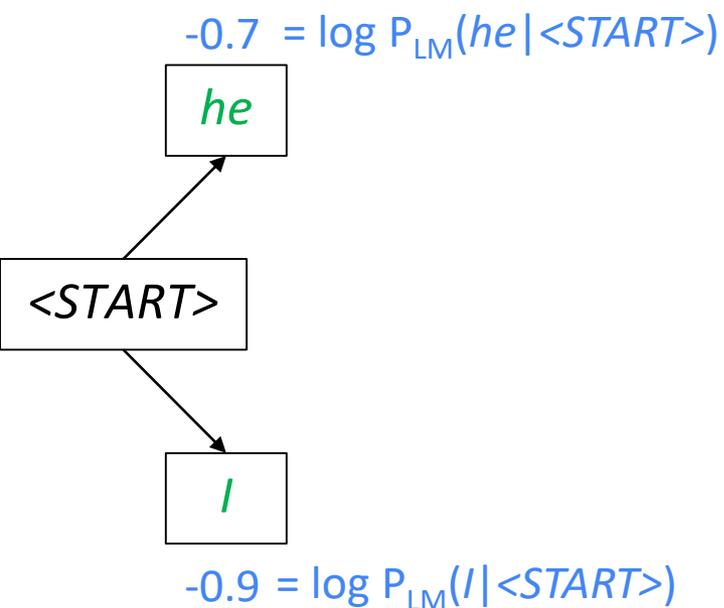
Beam size = $k = 2$. Blue numbers = $\text{score}(y_1, \dots, y_t) = \sum_{i=1}^t \log P_{\text{LM}}(y_i | y_1, \dots, y_{i-1}, x)$

<START>

Calculate prob
dist of next word

Beam search decoding: example

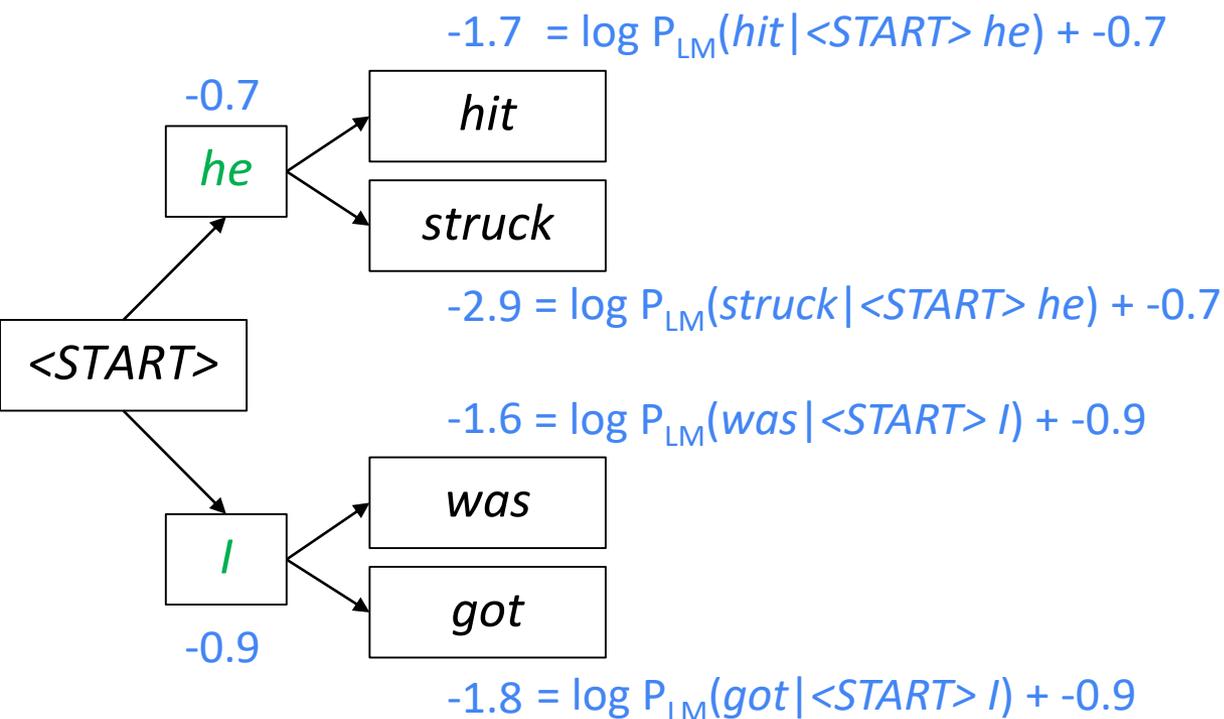
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Take top k words
and compute scores

Beam search decoding: example

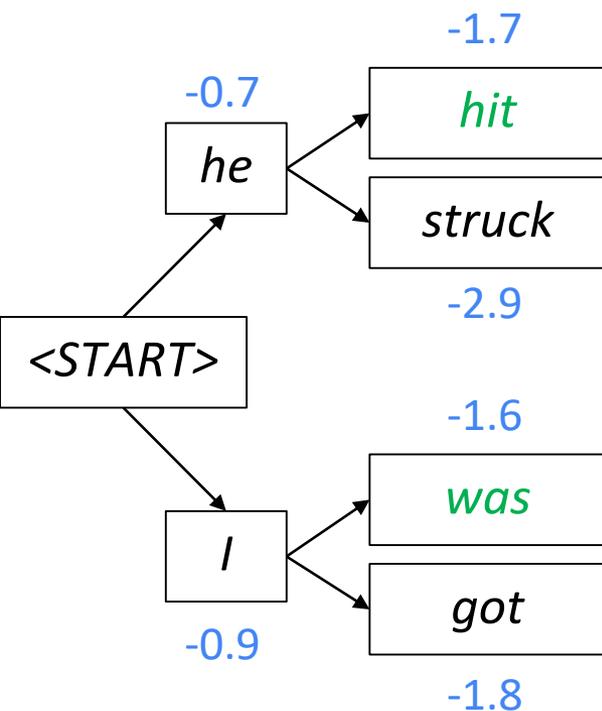
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For each of the k hypotheses, find top k next words and calculate scores

Beam search decoding: example

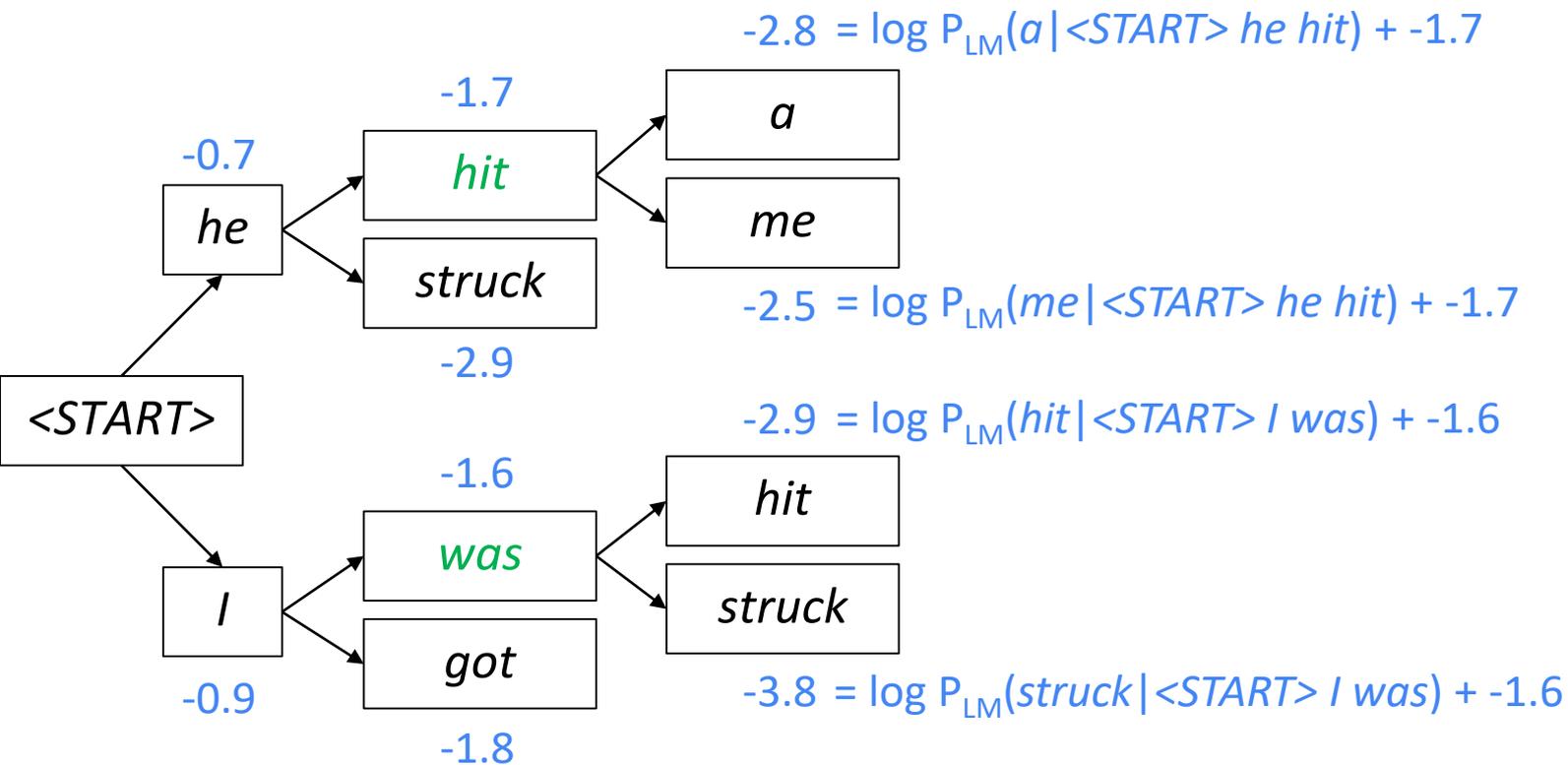
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Of these k^2 hypotheses,
just keep k with highest scores

Beam search decoding: example

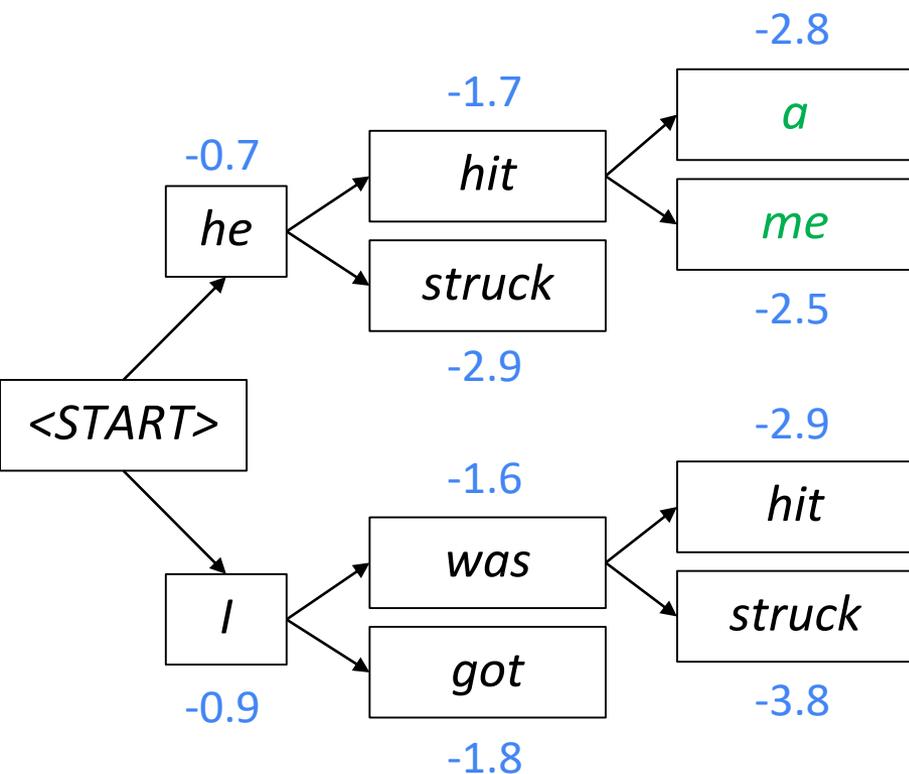
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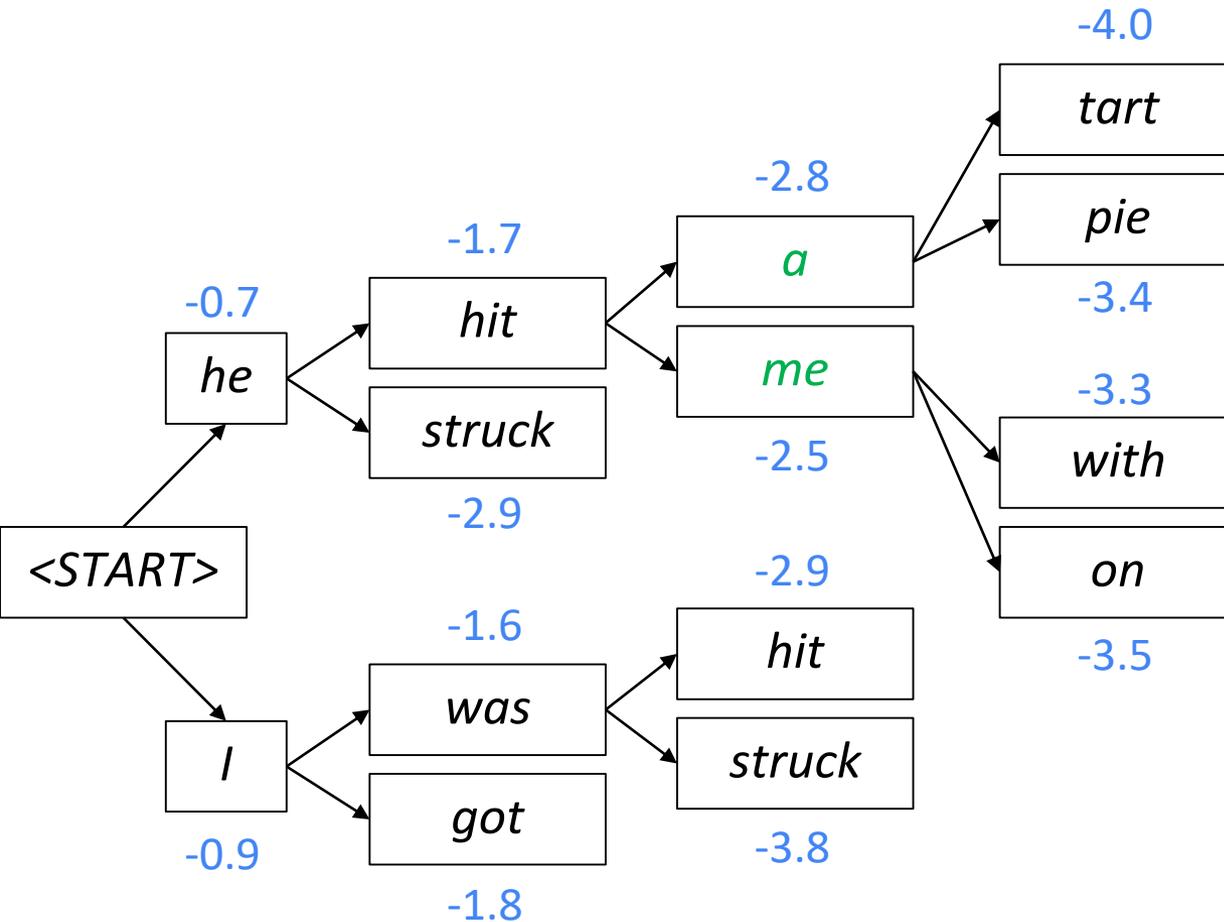
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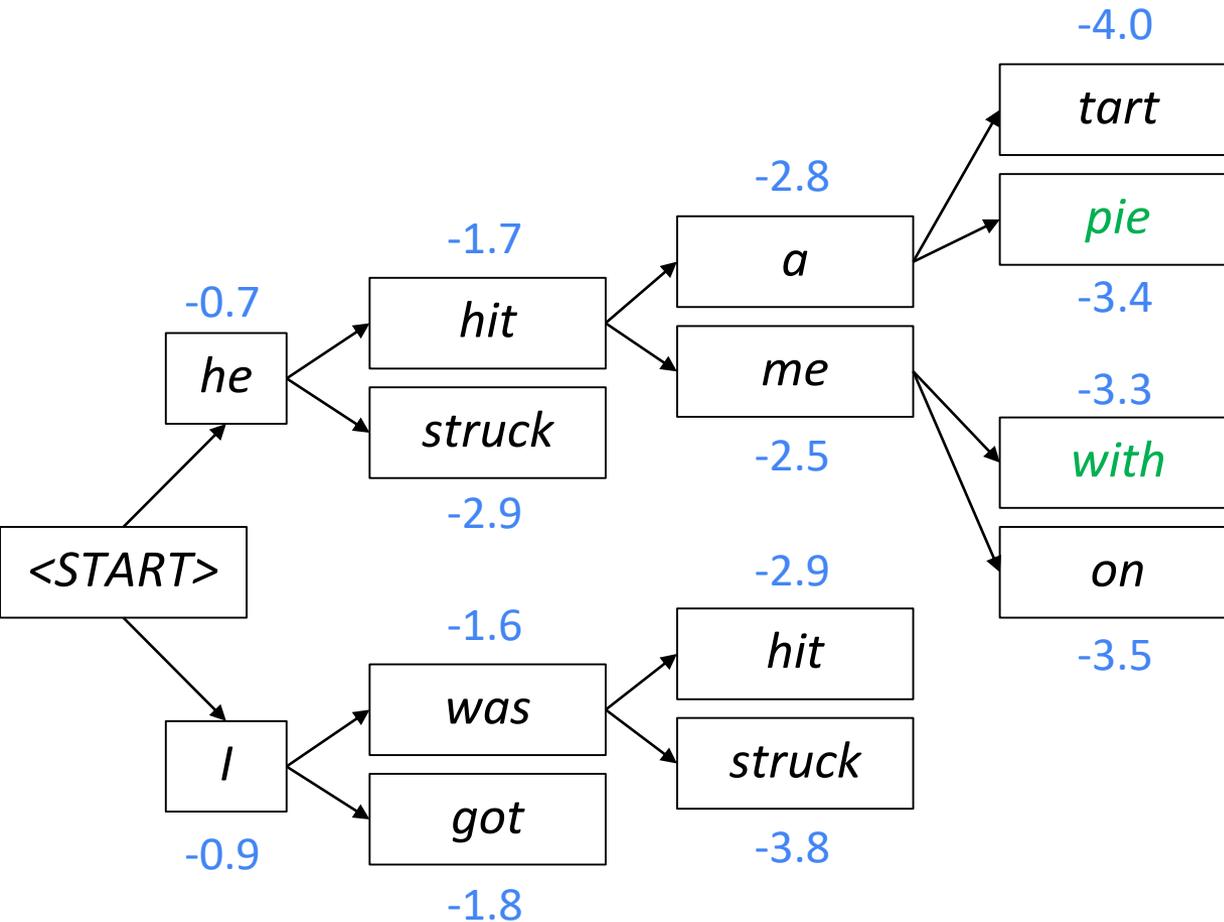
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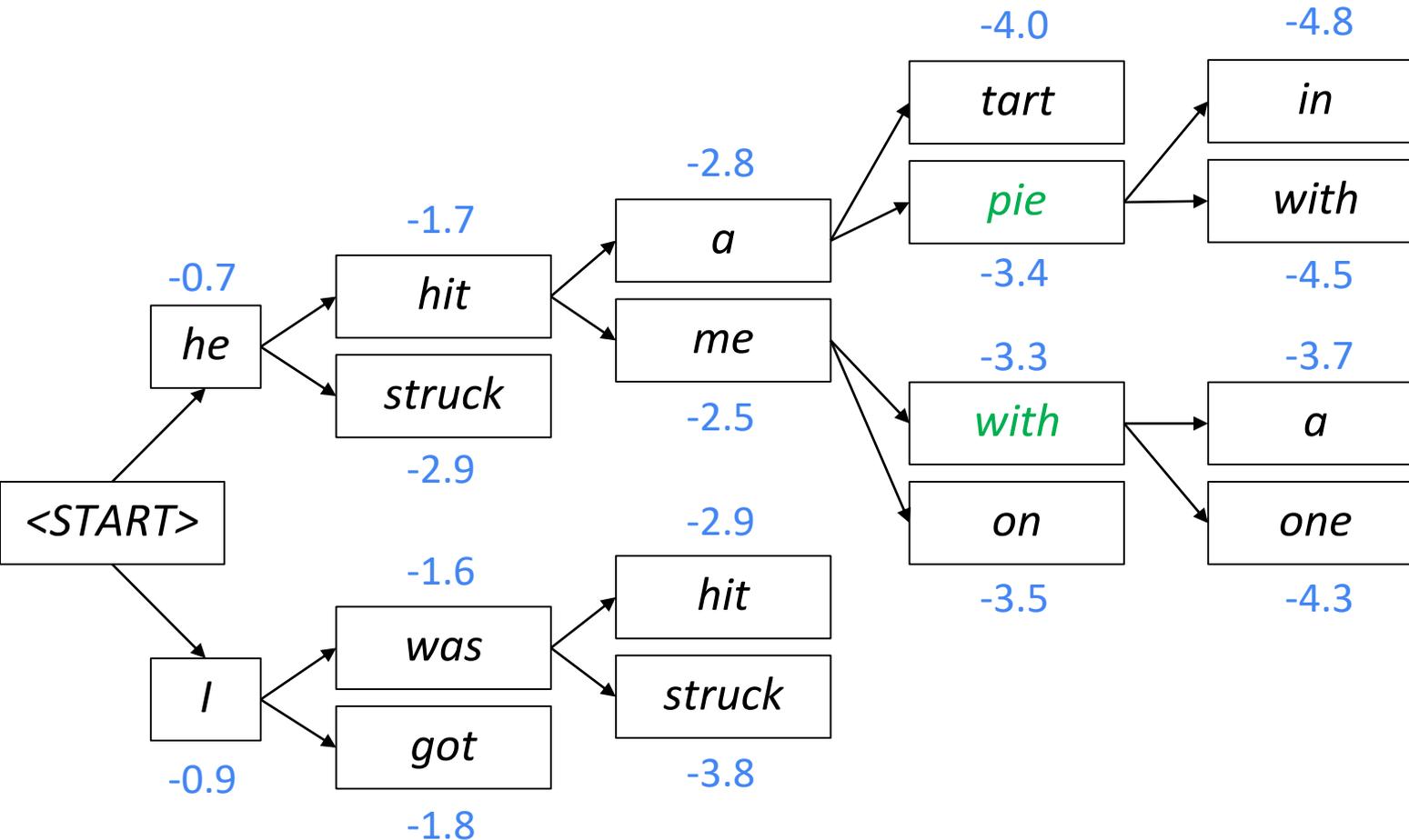
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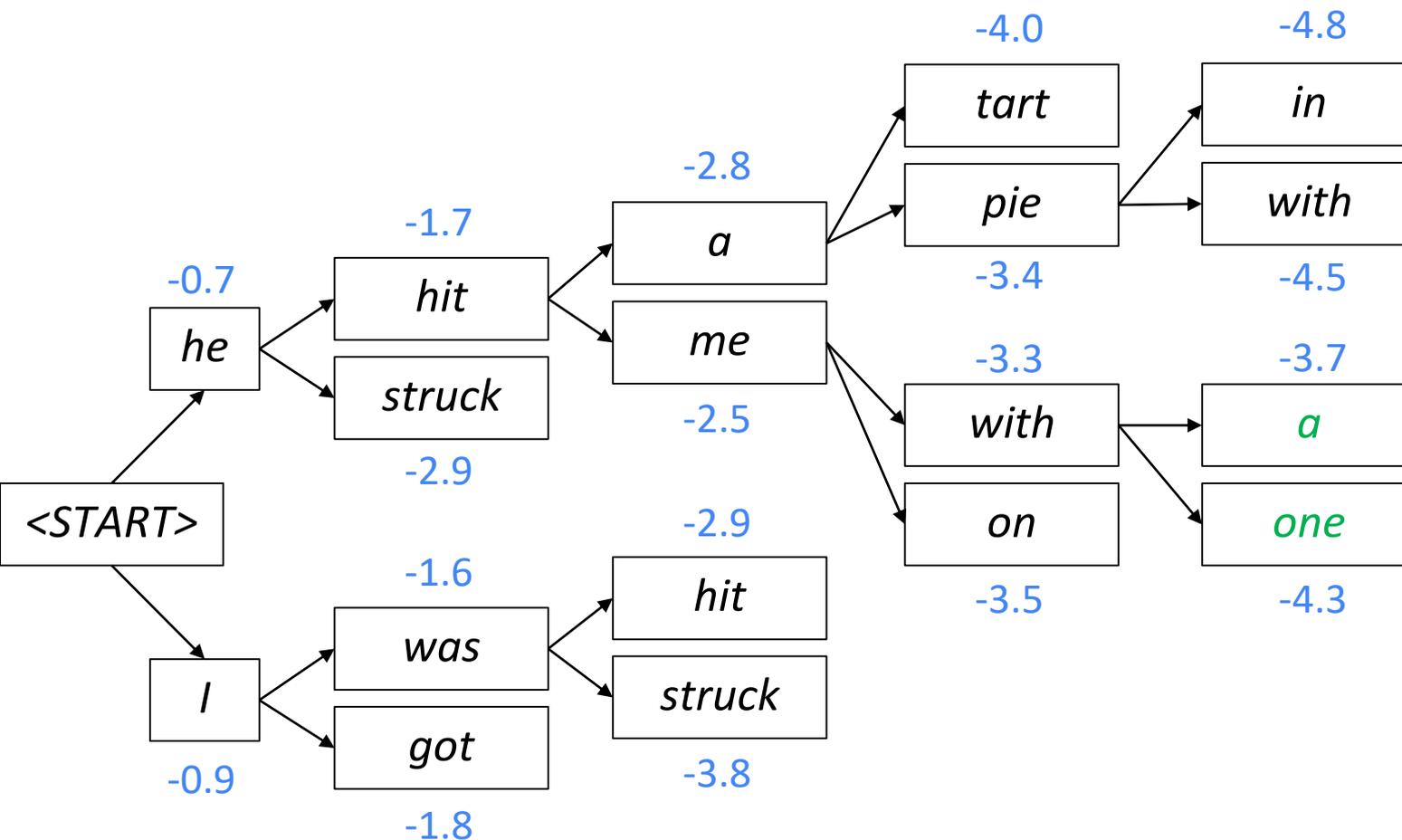
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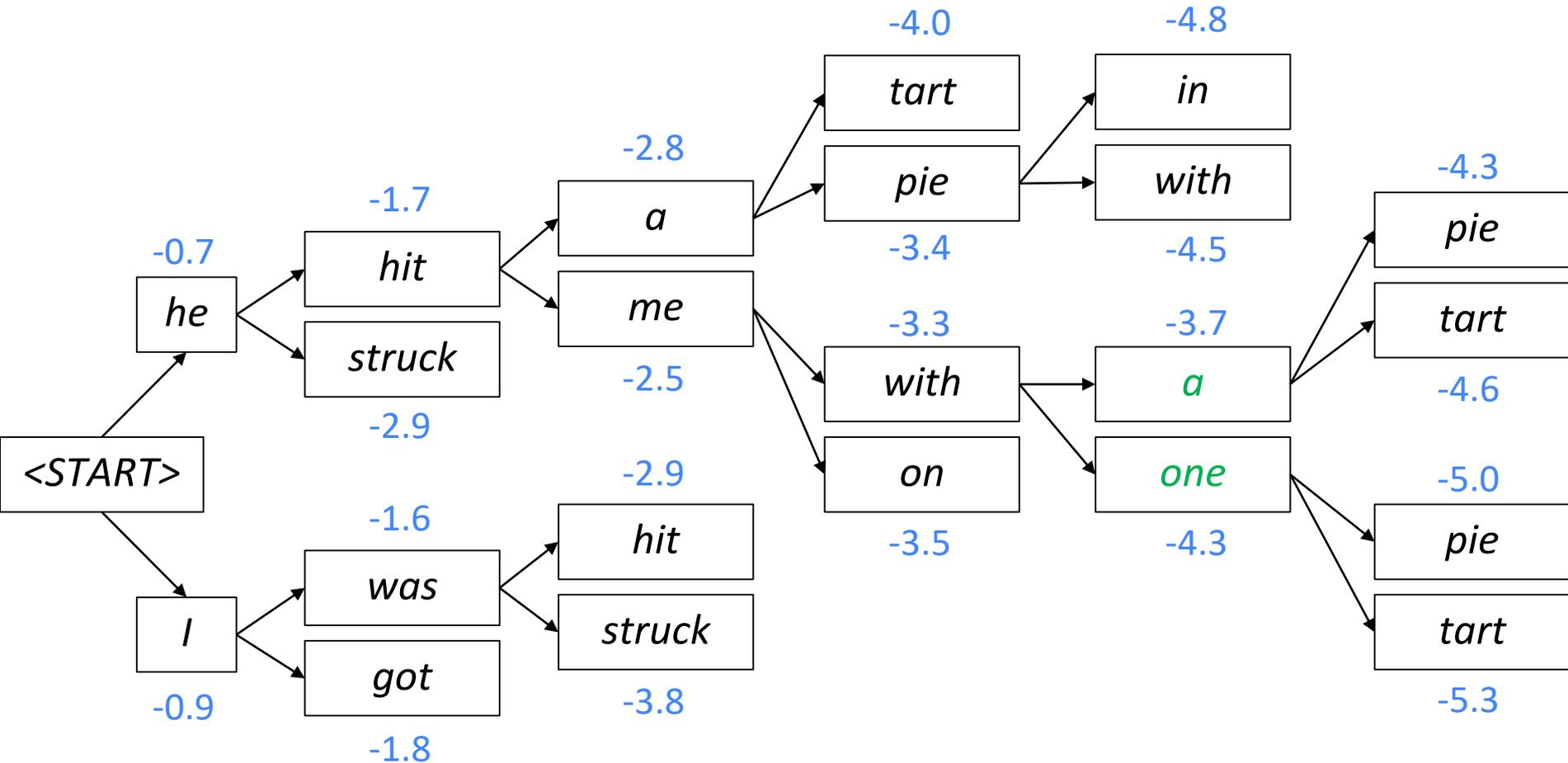
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Of these k^2 hypotheses, just keep k with highest scores

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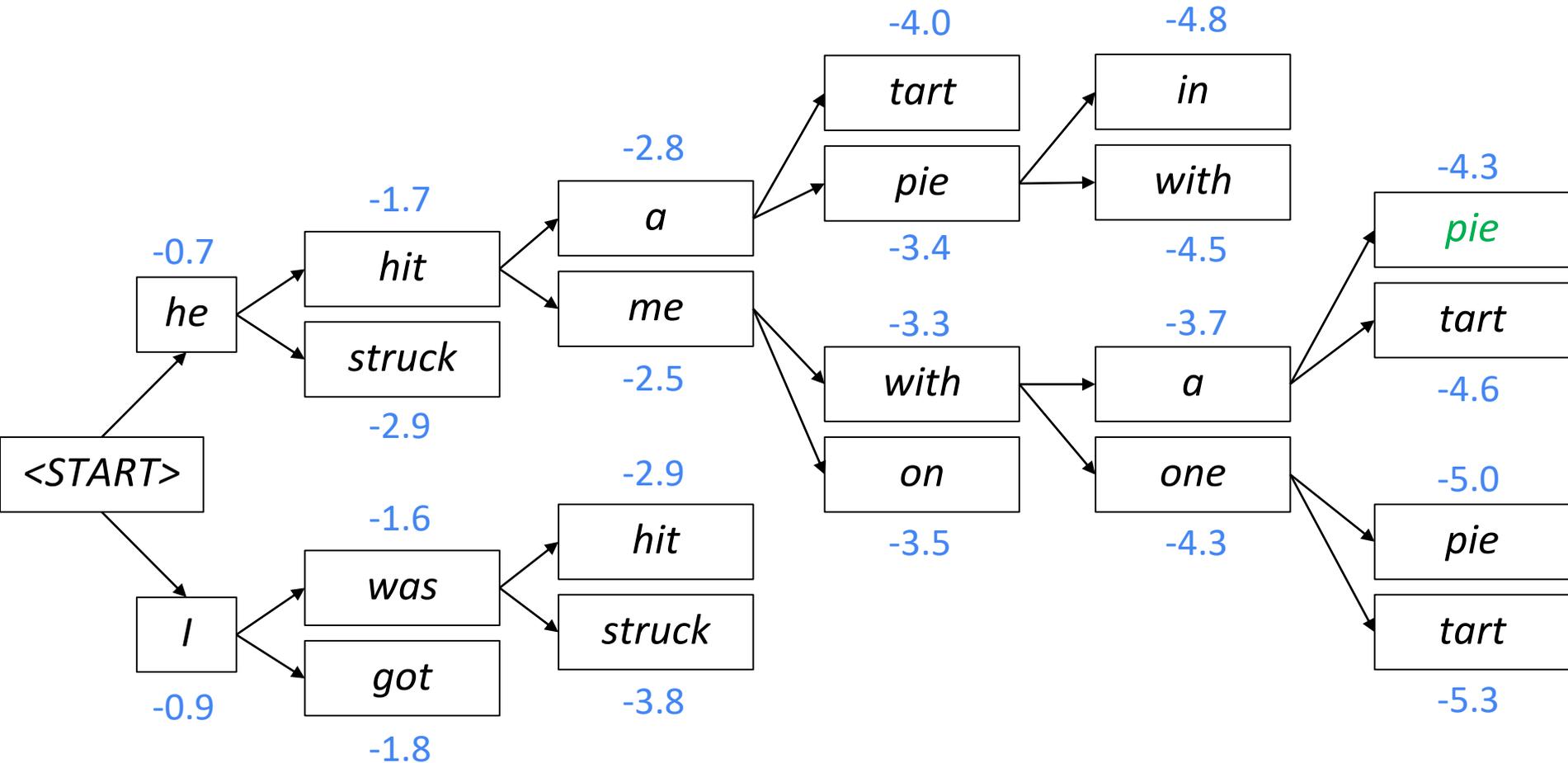
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Beam search decoding: example

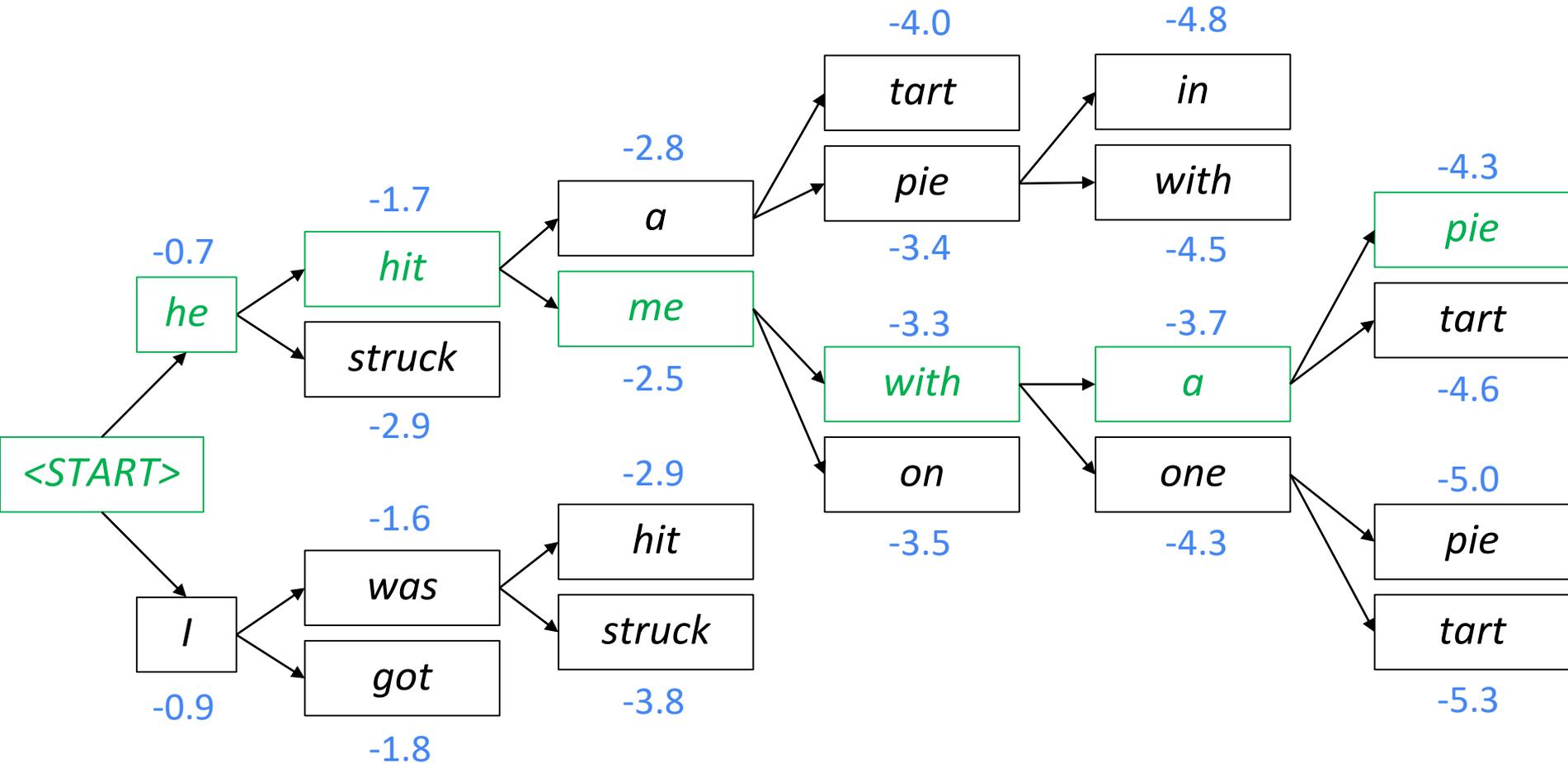
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This is the top-scoring hypothesis!

Beam search decoding: example

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



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, \dots, y_t on our list has a score

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

- Problem with this: longer hypotheses have lower scores
- Fix: Normalize by length. Use this to select top one instead:

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

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 (Bilingual Evaluation Understudy)

- 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 😞

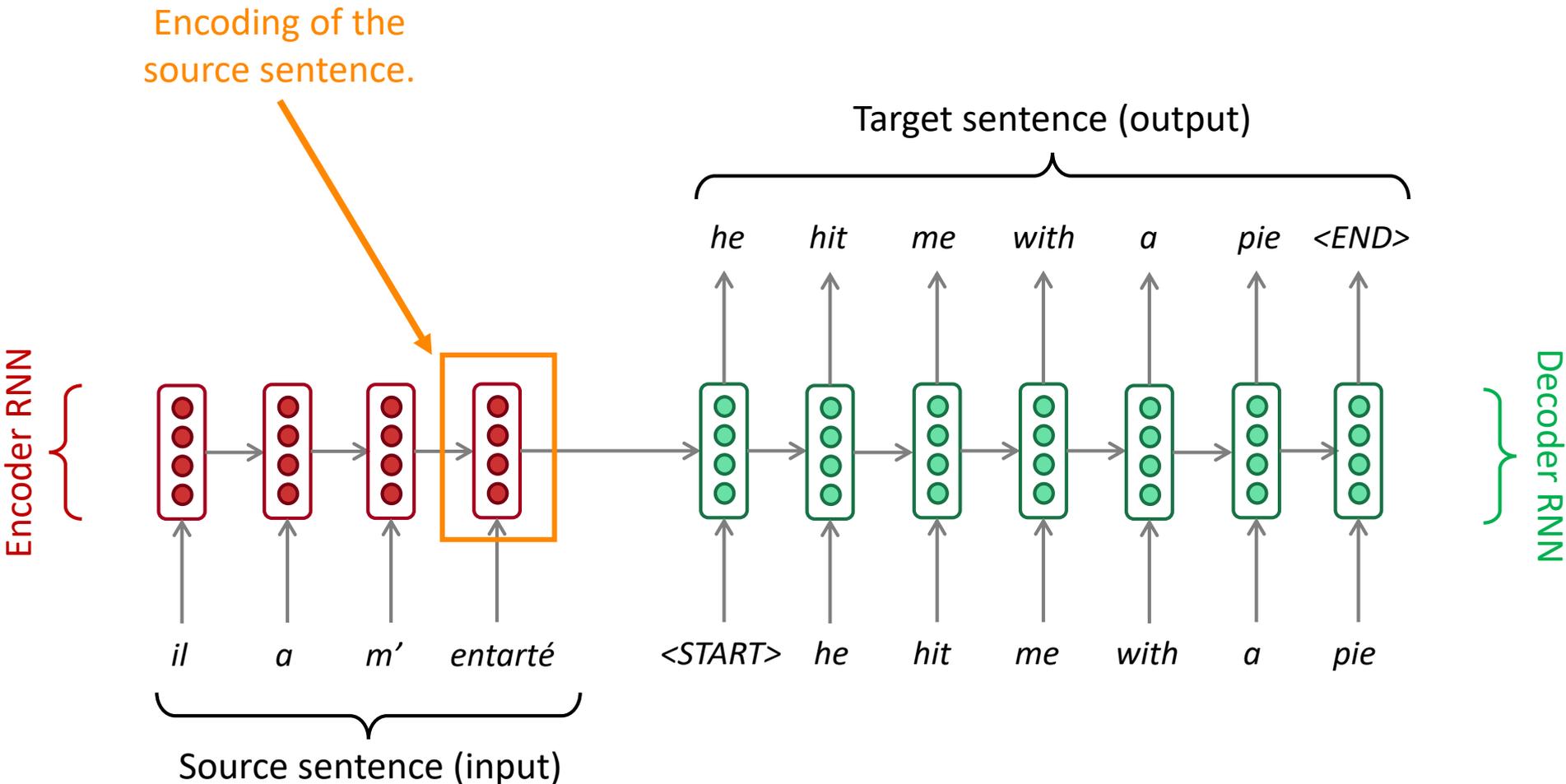
NMT: a big success story for NLP Deep Learning

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

- **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

Section 3: Attention

Sequence-to-sequence: the bottleneck problem



Problems with this architecture?

Sequence-to-sequence: the bottleneck problem

Encoding of the source sentence.

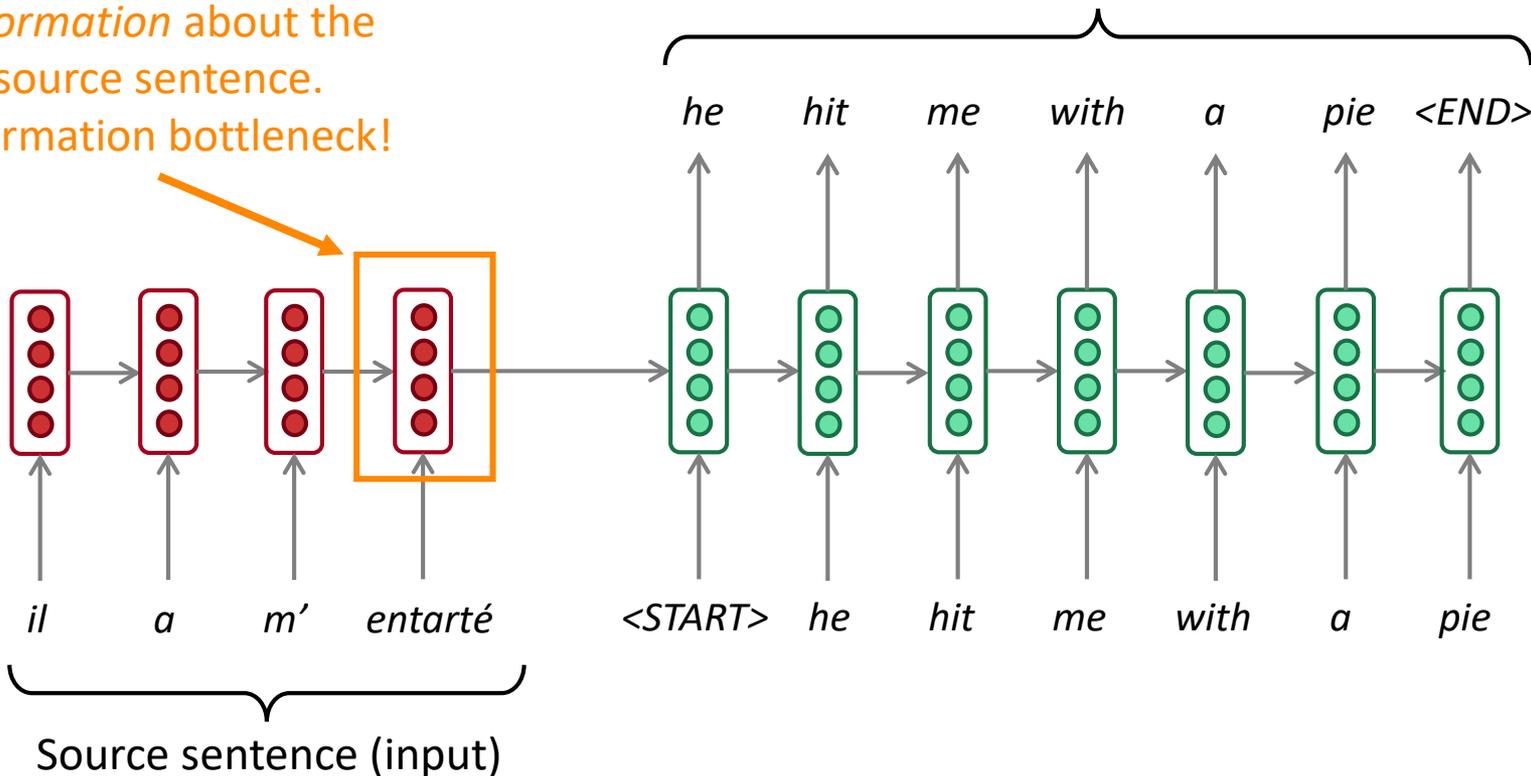
This needs to capture *all information* about the source sentence.

Information bottleneck!

Target sentence (output)

Encoder RNN

Decoder RNN



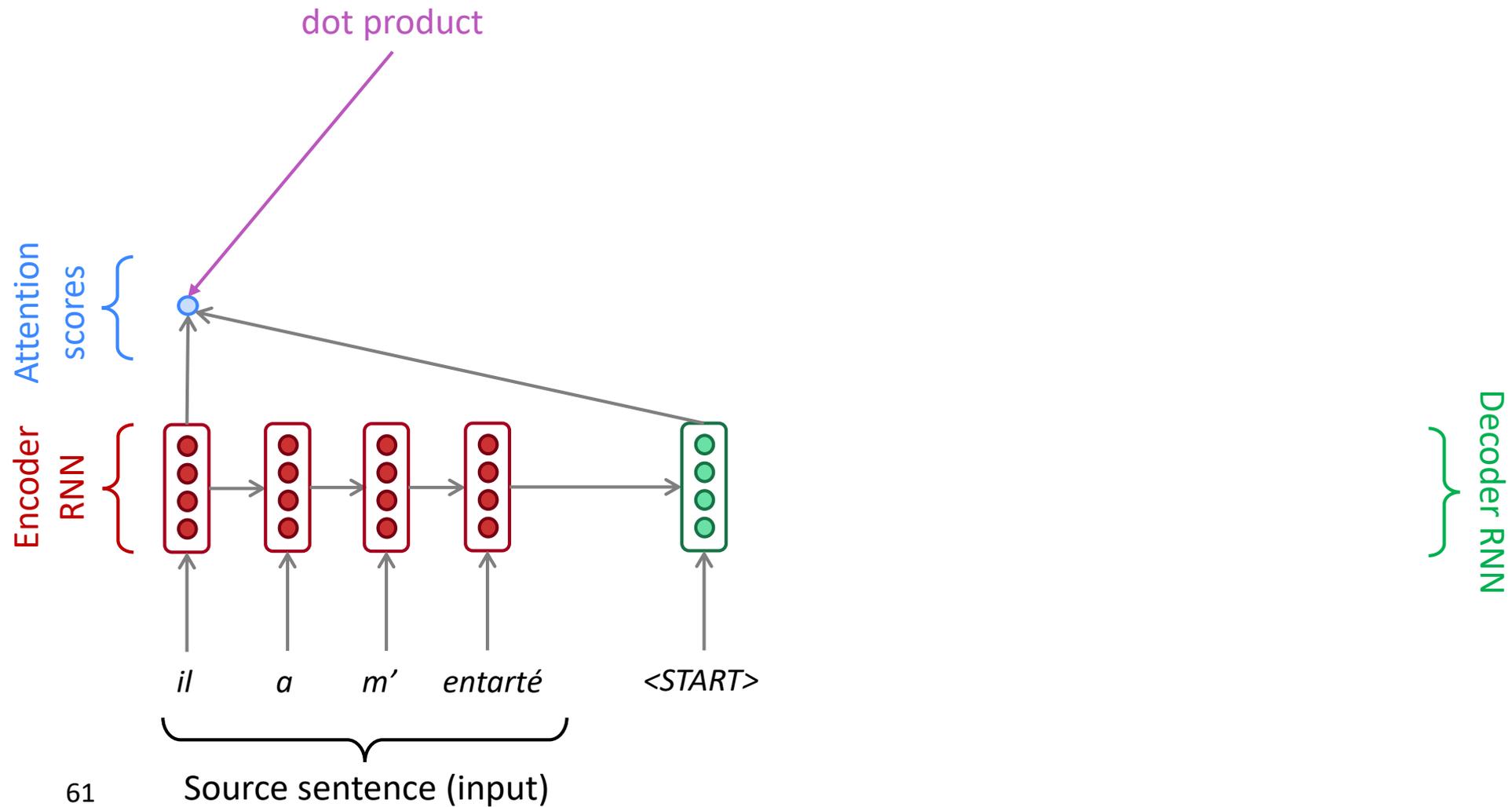
Attention

- **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

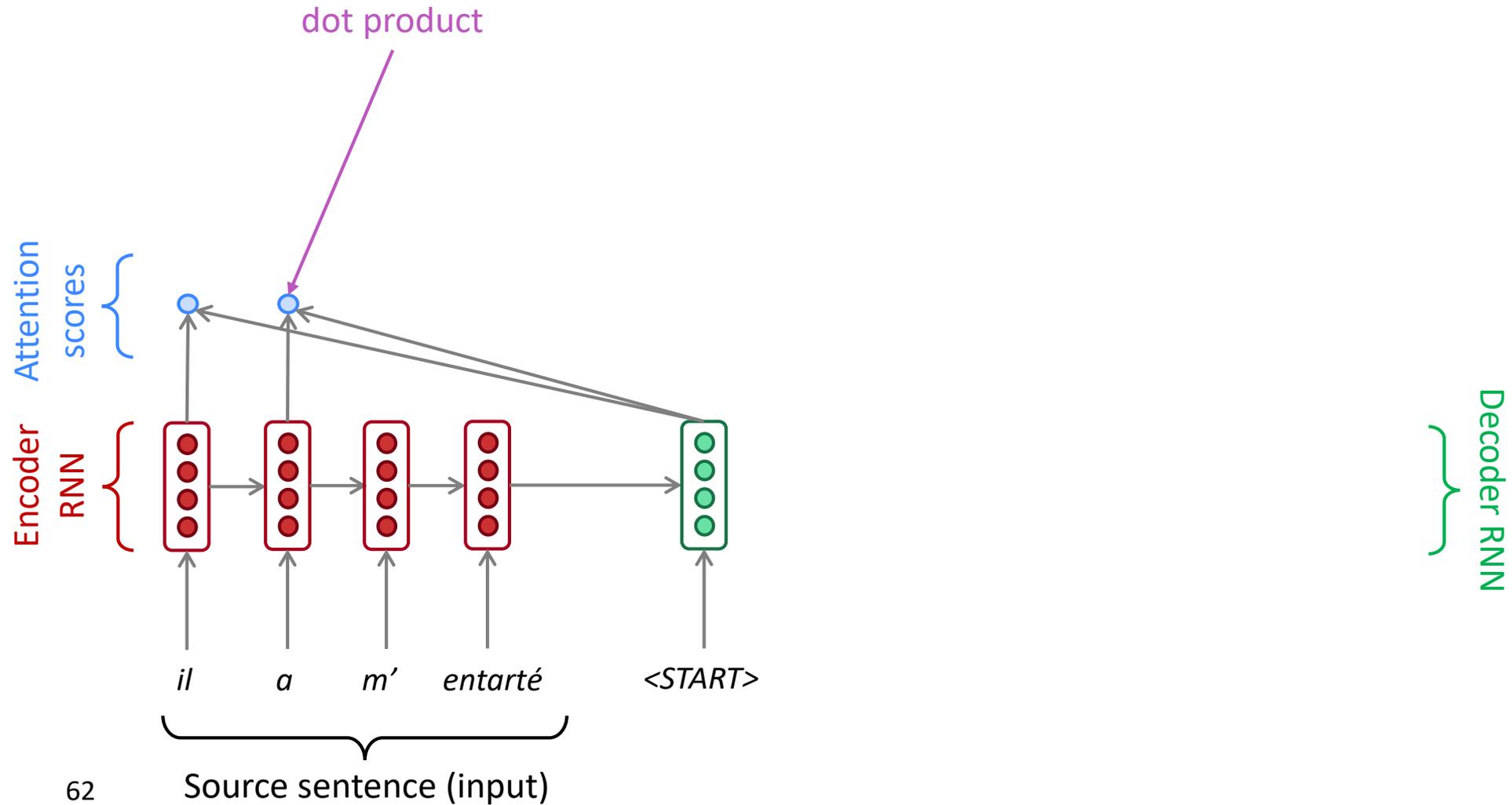


- First we will show via diagram (no equations), then we will show with equations

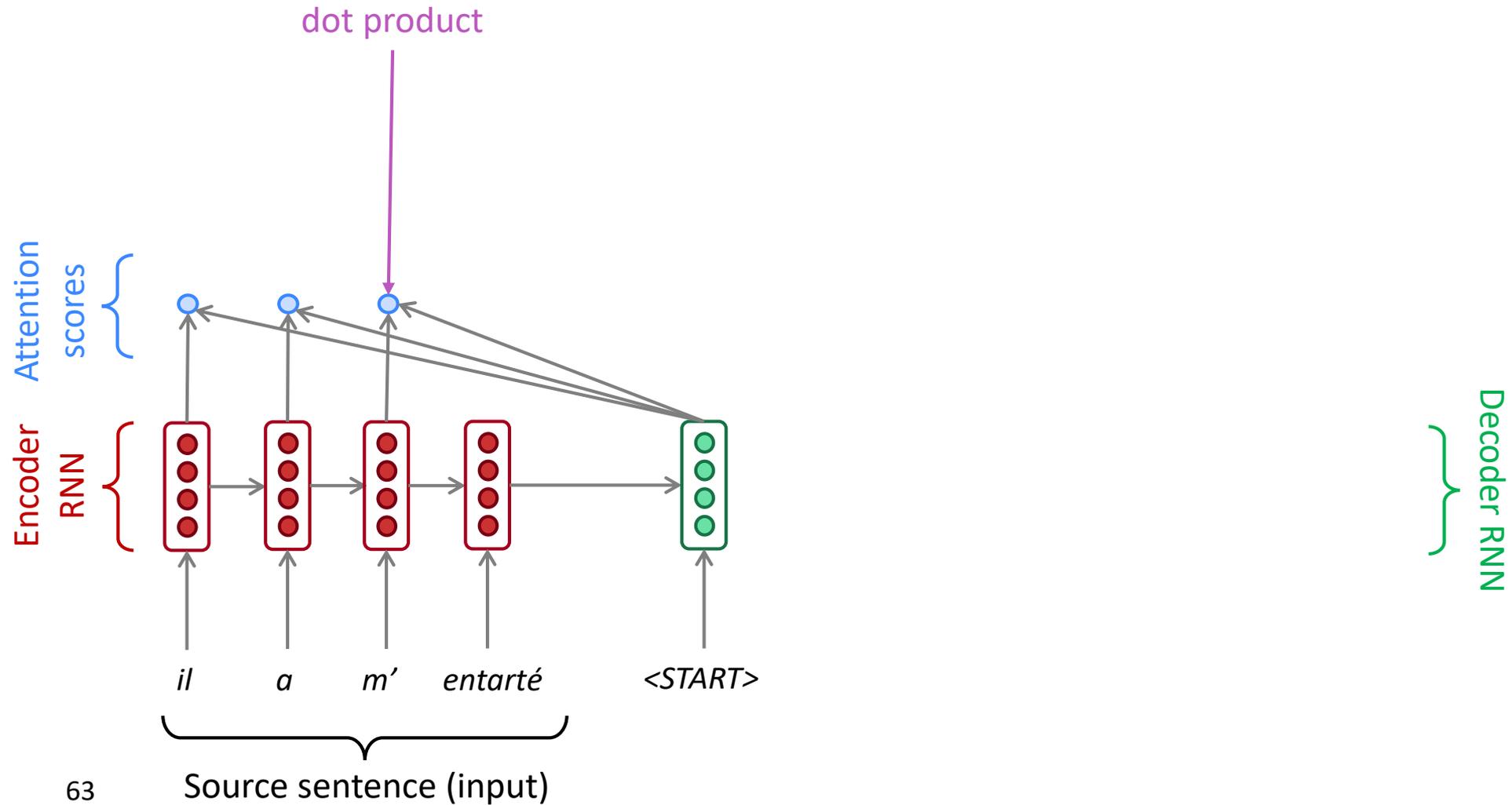
Sequence-to-sequence with attention



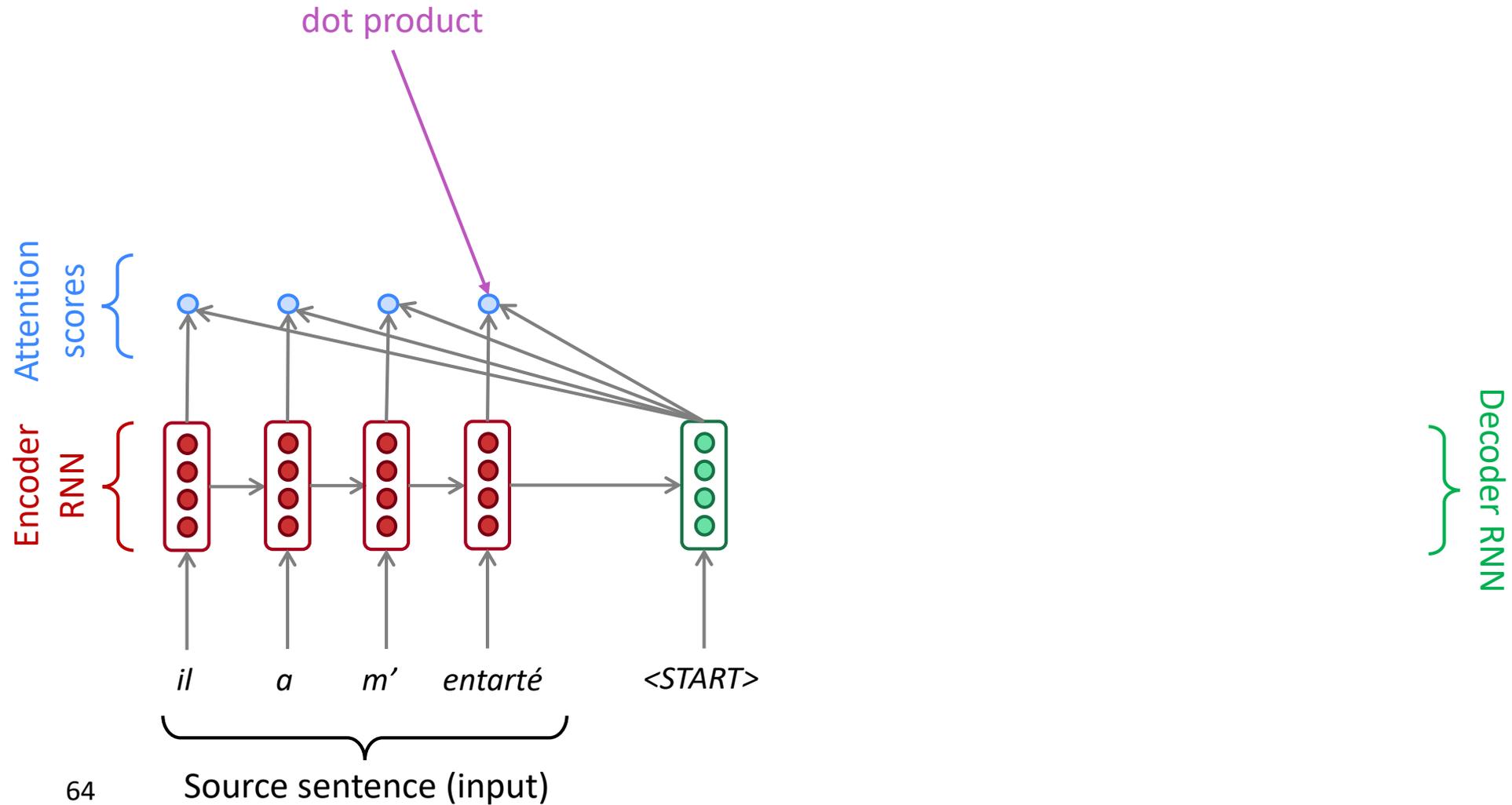
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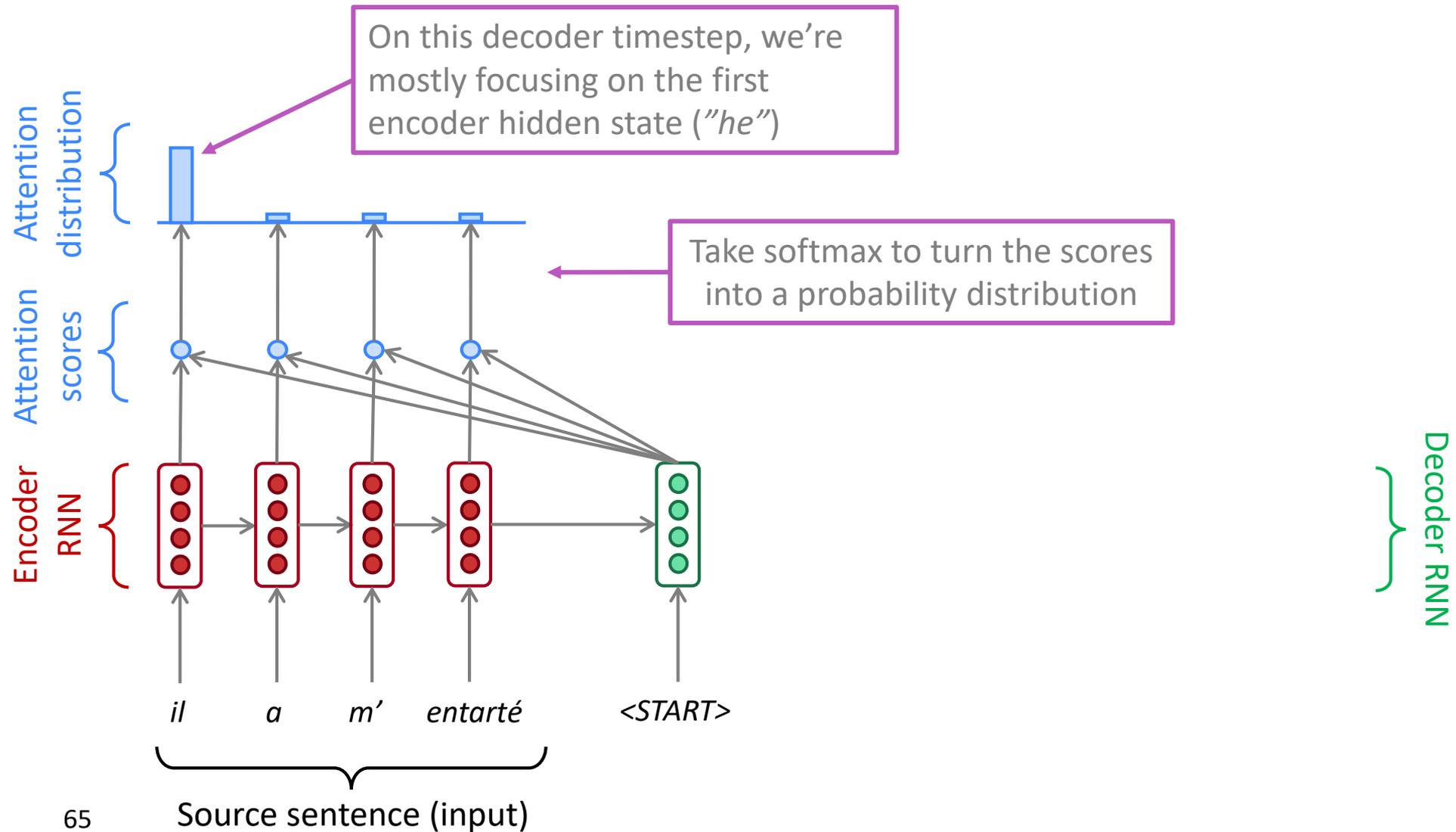
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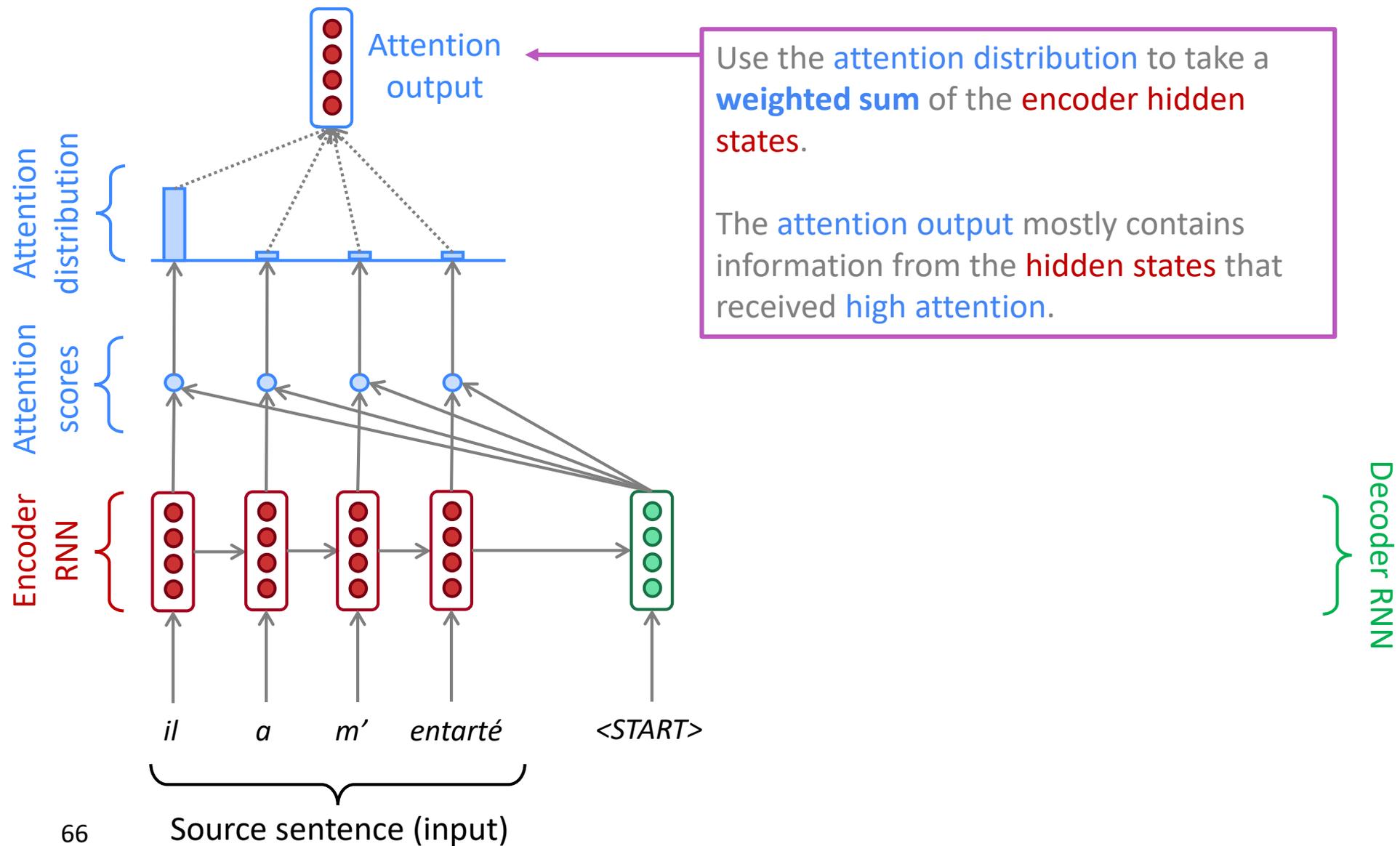
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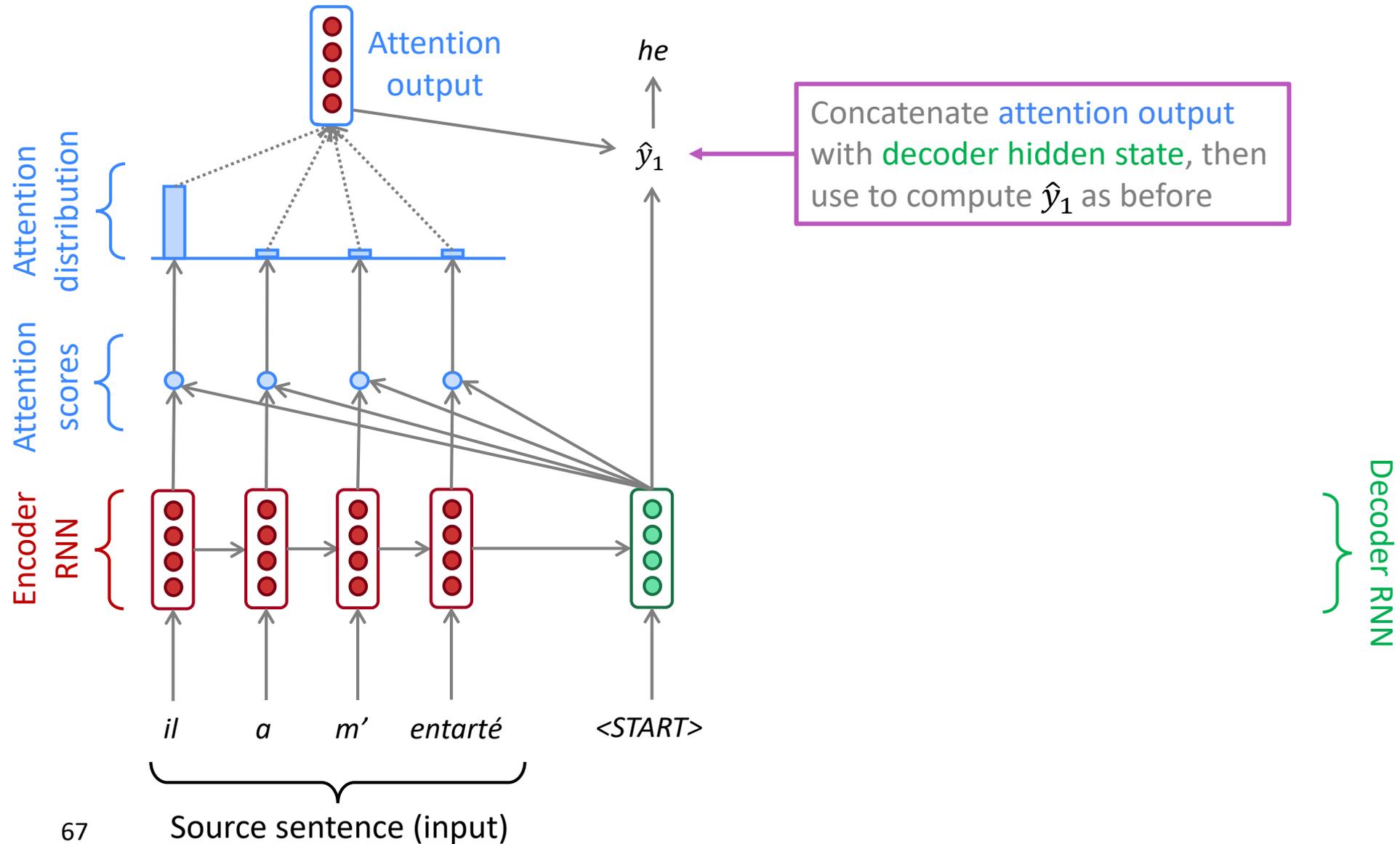
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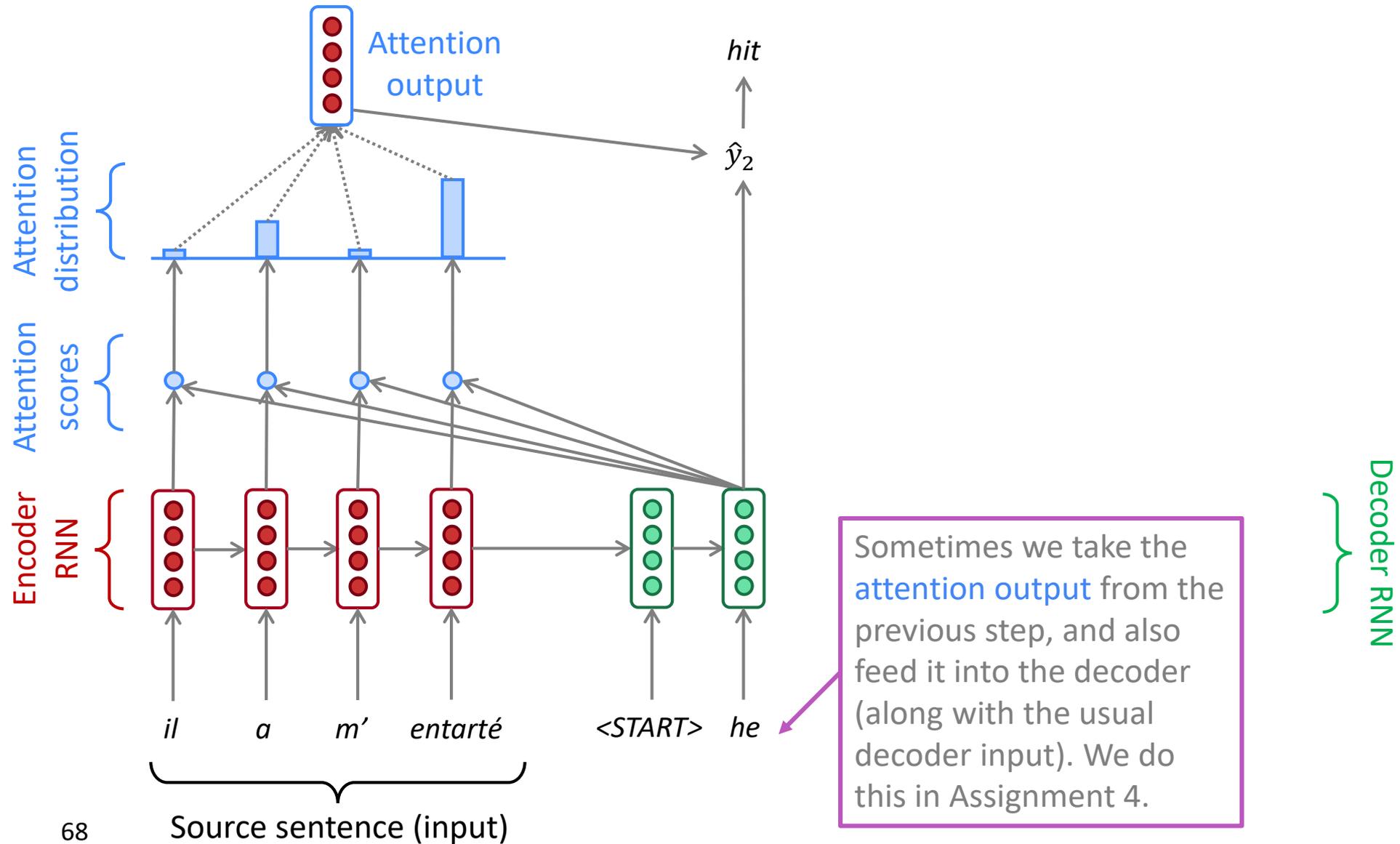
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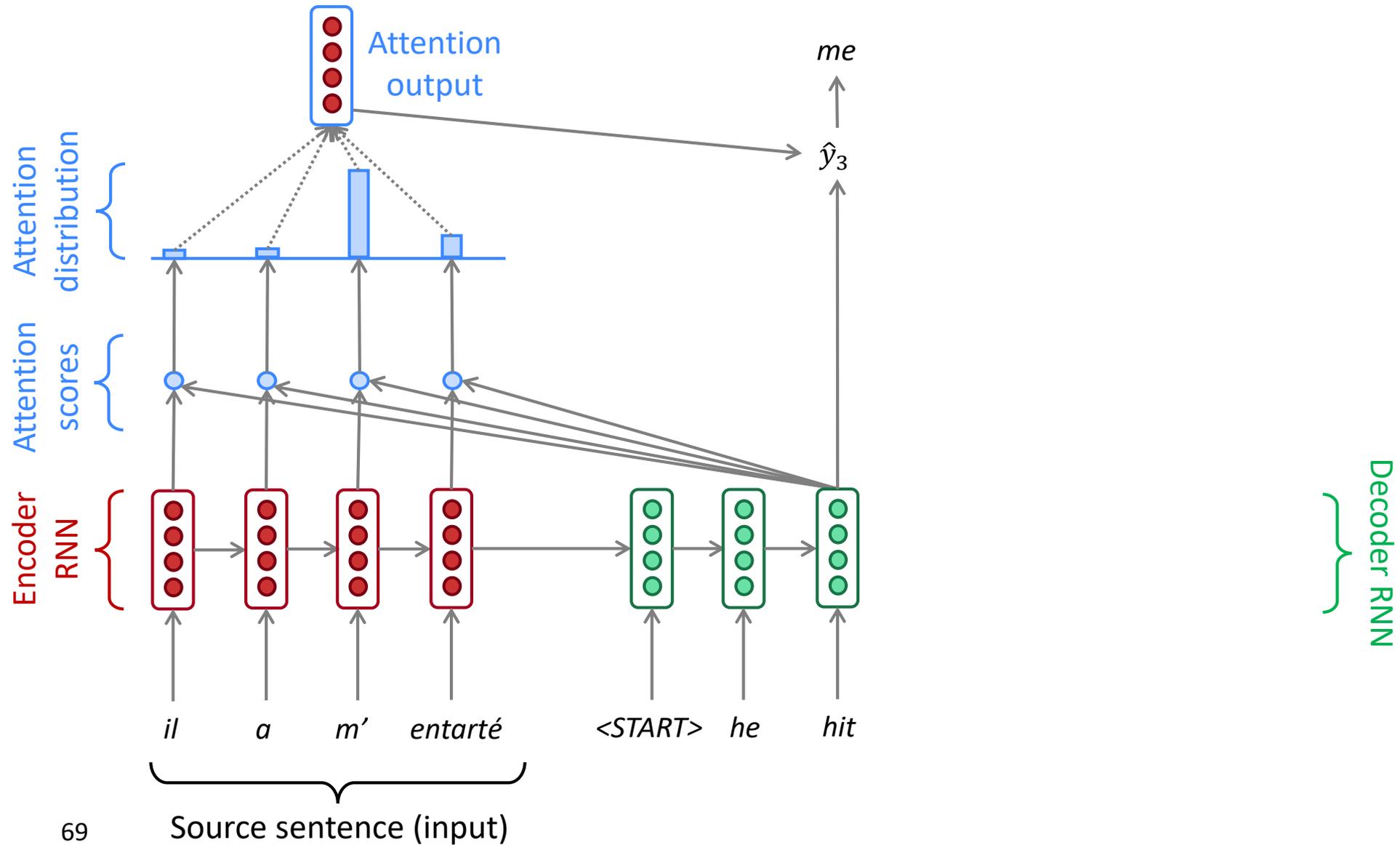
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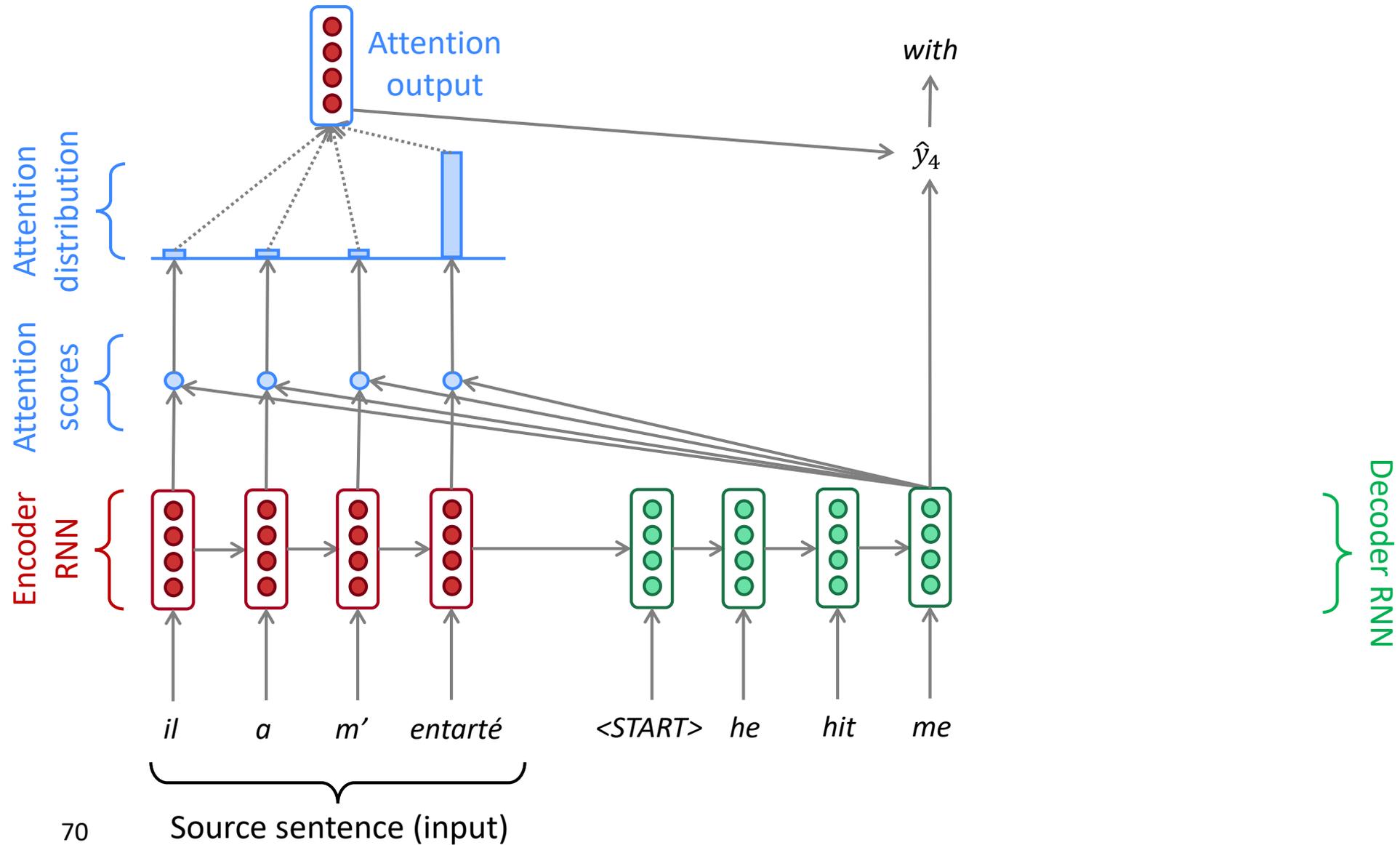
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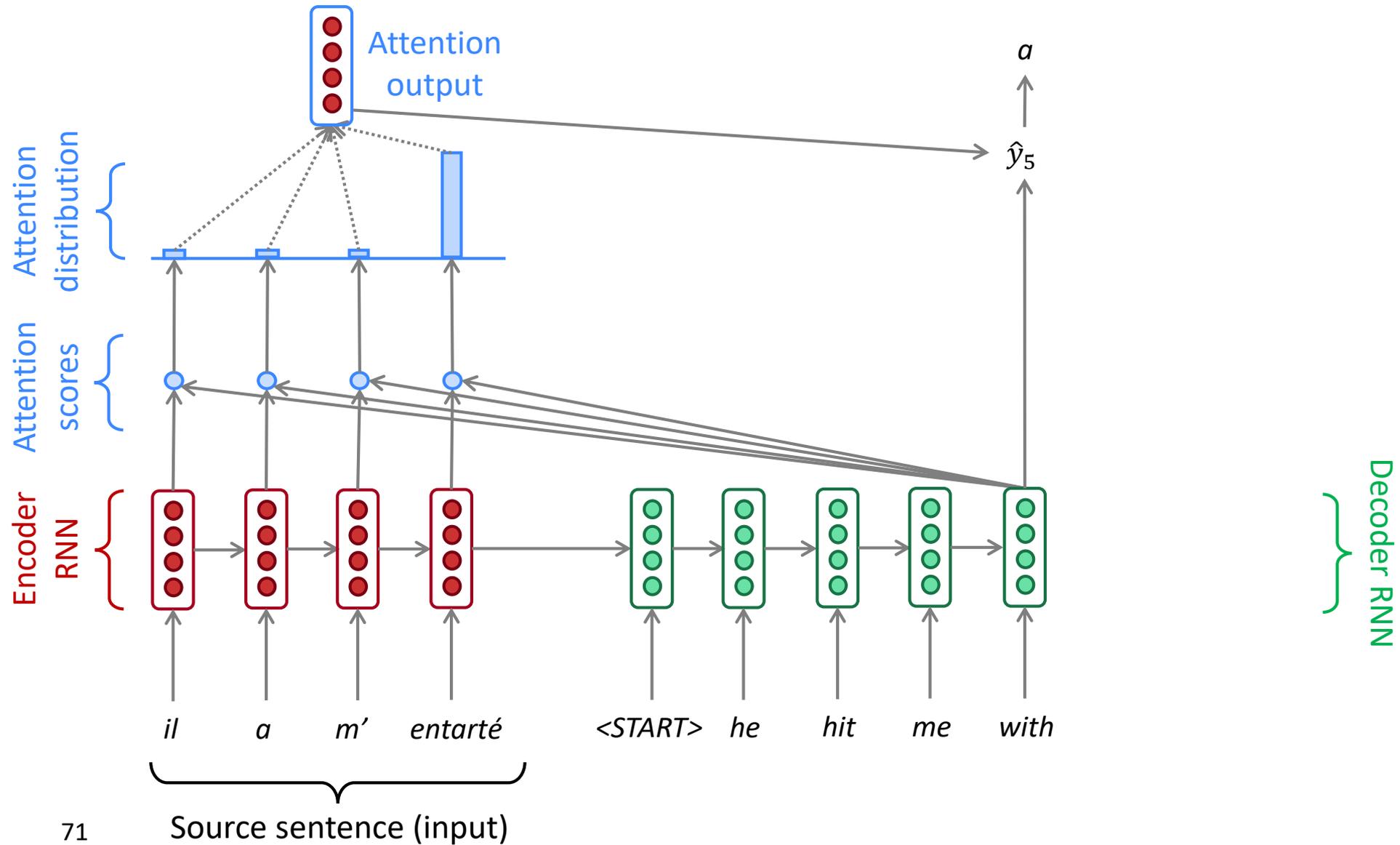
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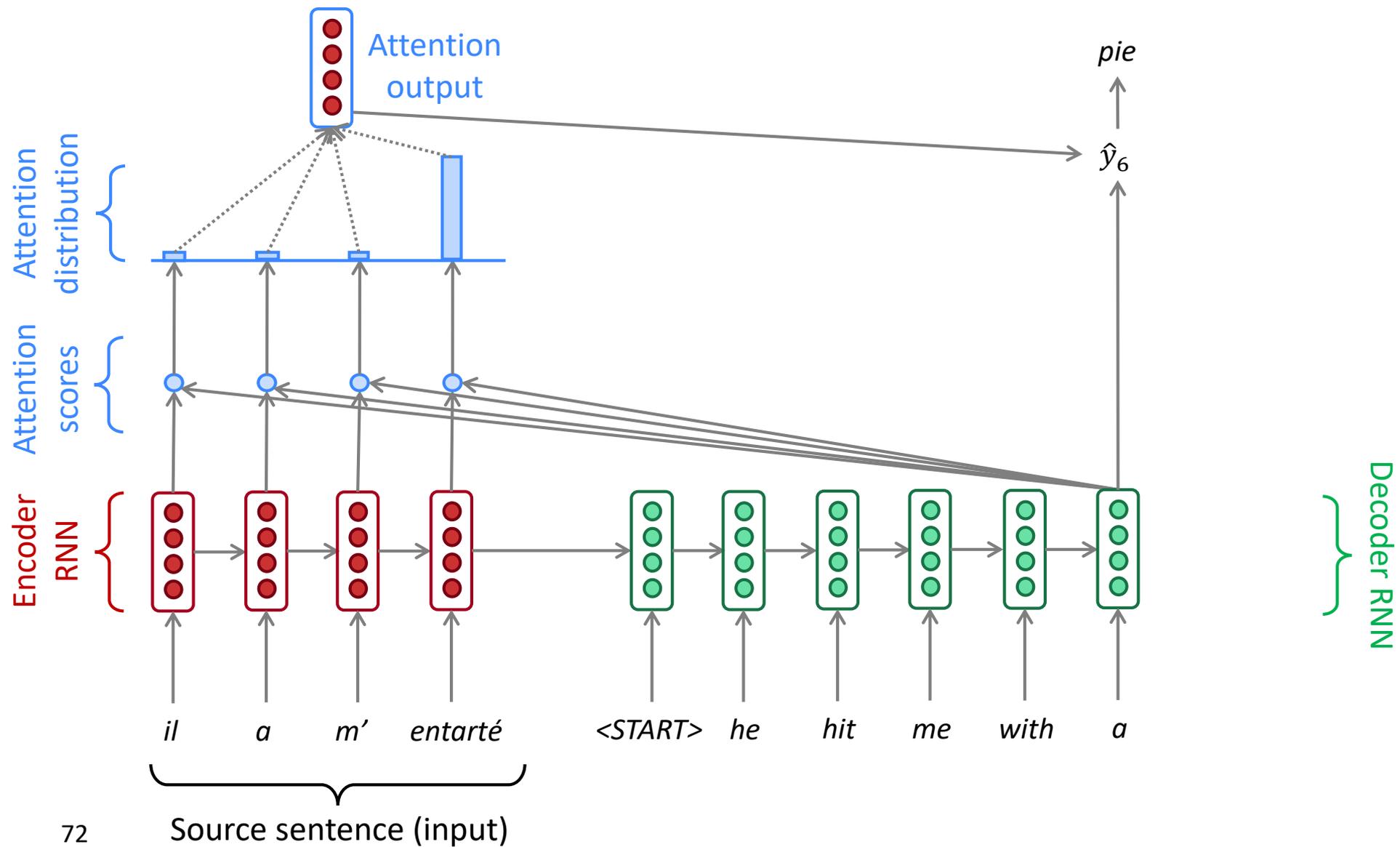
Sequence-to-sequence with attention



Sequence-to-sequence with attention



Sequence-to-sequence with attention



Attention: in equations

- We have encoder hidden states $h_1, \dots, h_N \in \mathbb{R}^h$
- On timestep t , we have decoder hidden state $s_t \in \mathbb{R}^h$
- We get the attention scores e^t for this step:

$$e^t = [s_t^T h_1, \dots, s_t^T h_N] \in \mathbb{R}^N$$

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

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

- We use α^t to take a weighted sum of the encoder hidden states to get the attention output a_t

$$a_t = \sum_{i=1}^N \alpha_i^t h_i \in \mathbb{R}^h$$

- Finally we concatenate the attention output a_t with the decoder hidden state s_t and proceed as in the non-attention seq2seq model

$$[a_t; s_t] \in \mathbb{R}^{2h}$$

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

	he	hit	me	with	a	pie
il	■	□	□	□	□	□
a	□	■	□	□	□	□
m'	□	□	■	□	□	□
entarté	□	■	■	■	■	■

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.
- However: You can use attention in **many architectures** (not just seq2seq) and **many tasks** (not just MT)

- 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.

- 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* $\mathbf{h}_1, \dots, \mathbf{h}_N \in \mathbb{R}^{d_1}$ and a *query* $\mathbf{s} \in \mathbb{R}^{d_2}$

- Attention always involves:

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

There are multiple ways to do this

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

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

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

thus obtaining the *attention output* \mathbf{a} (sometimes called the *context vector*)

Attention variants

There are **several ways** you can compute $e \in \mathbb{R}^N$ from $\mathbf{h}_1, \dots, \mathbf{h}_N \in \mathbb{R}^{d_1}$ and $\mathbf{s} \in \mathbb{R}^{d_2}$:

- Basic dot-product attention: $e_i = \mathbf{s}^T \mathbf{h}_i \in \mathbb{R}$
 - Note: this assumes $d_1 = d_2$
 - This is the version we saw earlier
- Multiplicative attention: $e_i = \mathbf{s}^T \mathbf{W} \mathbf{h}_i \in \mathbb{R}$
 - Where $\mathbf{W} \in \mathbb{R}^{d_2 \times d_1}$ is a weight matrix
- Additive attention: $e_i = \mathbf{v}^T \tanh(\mathbf{W}_1 \mathbf{h}_i + \mathbf{W}_2 \mathbf{s}) \in \mathbb{R}$
 - Where $\mathbf{W}_1 \in \mathbb{R}^{d_3 \times d_1}$, $\mathbf{W}_2 \in \mathbb{R}^{d_3 \times d_2}$ are weight matrices and $\mathbf{v} \in \mathbb{R}^{d_3}$ 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/1703.03906.pdf>

Summary of today's lecture

- 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!

