CIS 6930 Special Topics in Large Language Models

Sequence-to-Sequence LM

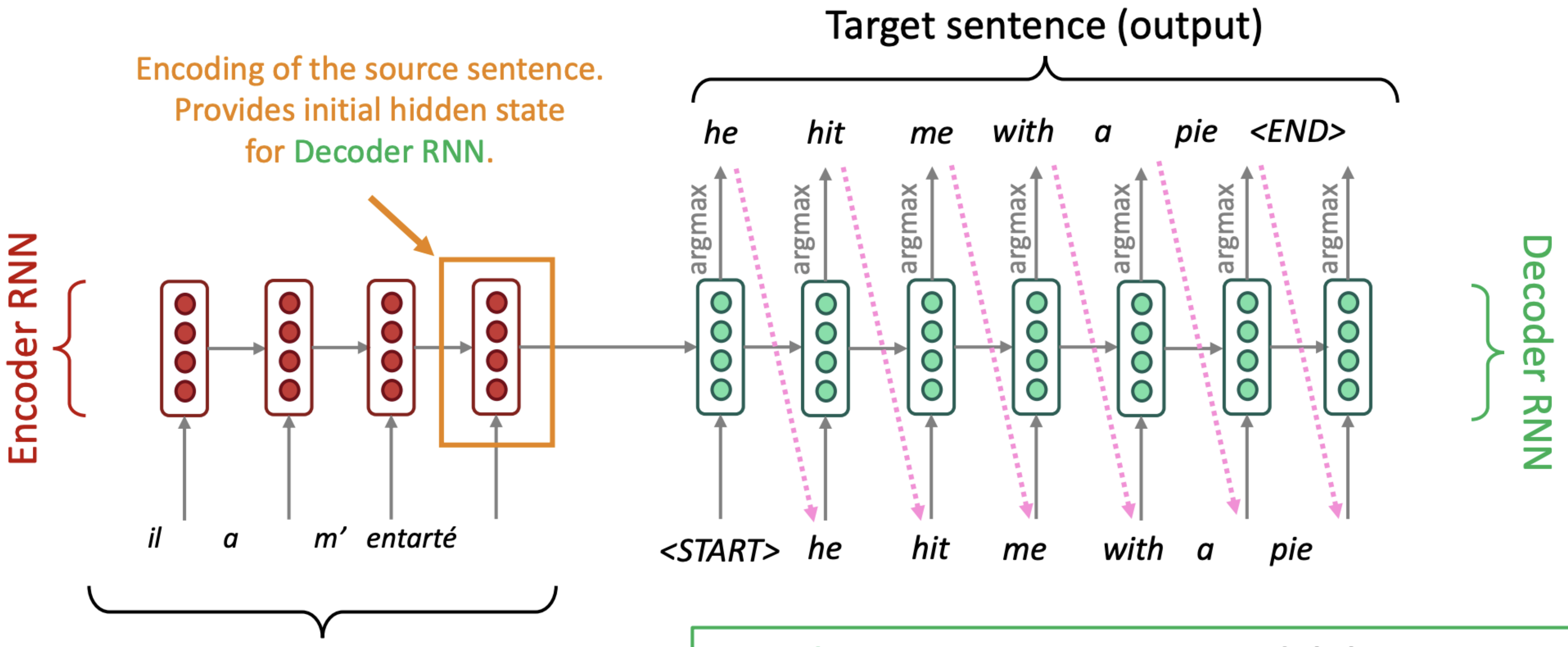
Outline

- Sequence-to-Sequence Language Model
- Sequence-to-Sequence with Attention

Sequence-to-Sequence LM

Sequence-to-Sequence

Machine Translation



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

- The general notion here is an encoder-decoder model
  - One neural network takes input and produces a neural representation
  - Another network produces output based on that neural representation
  - If the input and output are sequences, we call it a seq2seq model

- 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)

Sequence-to-Sequence

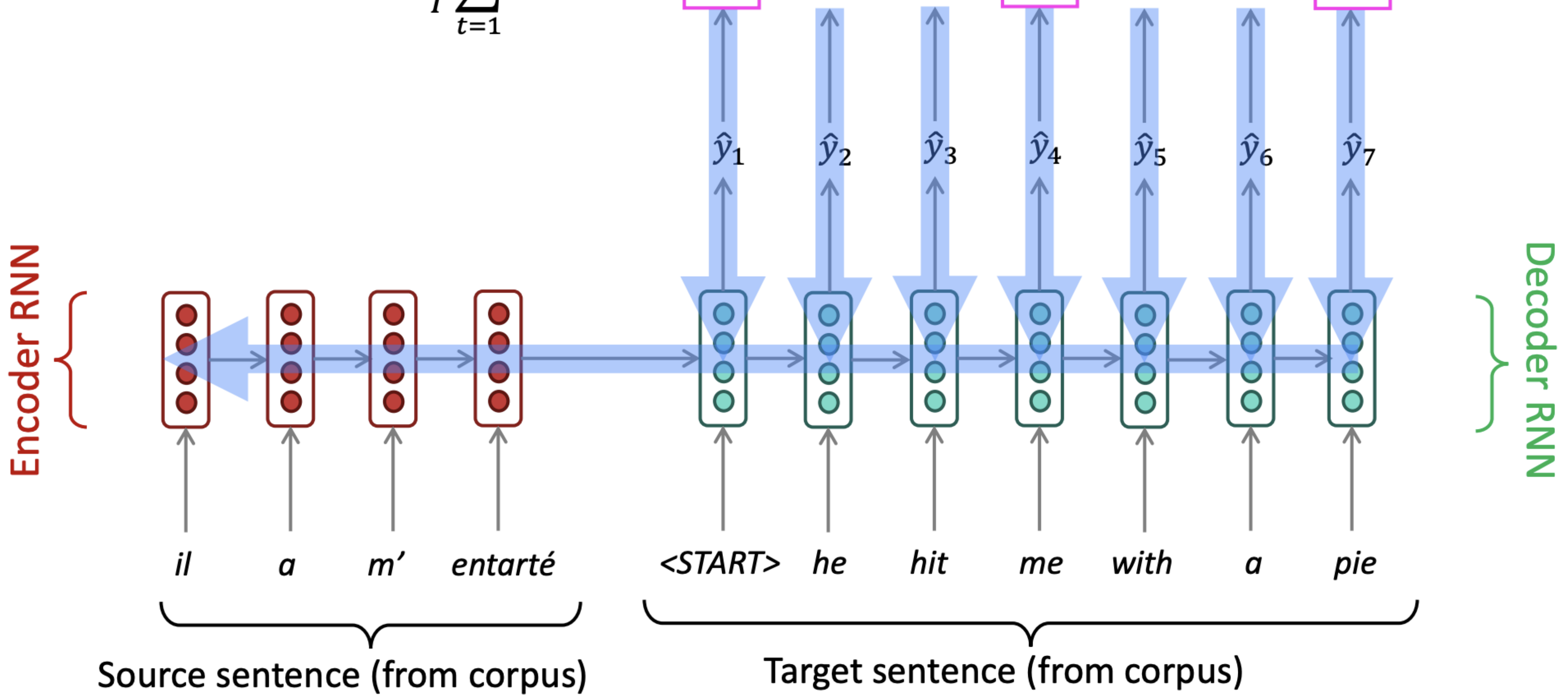
- The sequence-to-sequence model is an example of a **Conditional Language Model**
  - **Language Model** because the decoder is predicting the next word of the target sentence *y*
  - **Conditional** because its predictions are *also* conditioned on the source sentence *x*

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

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

Training Sequence-to-Sequence

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

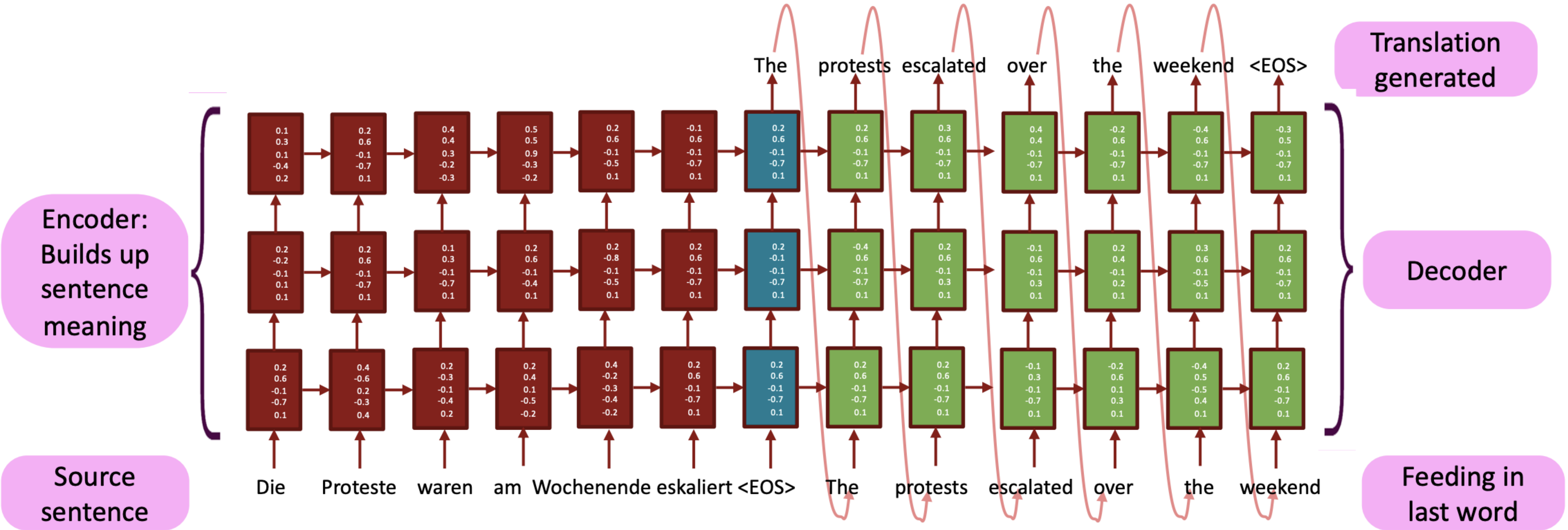


Seq2seq is optimized as a **single system.** Backpropagation operates *"end-to-end"*.

Multi-layer Sequence-to-Sequence

[Sutskever et al. 2014; Luong et al. 2015]

The hidden states from RNN layer *i* are the inputs to RNN layer *i*+1

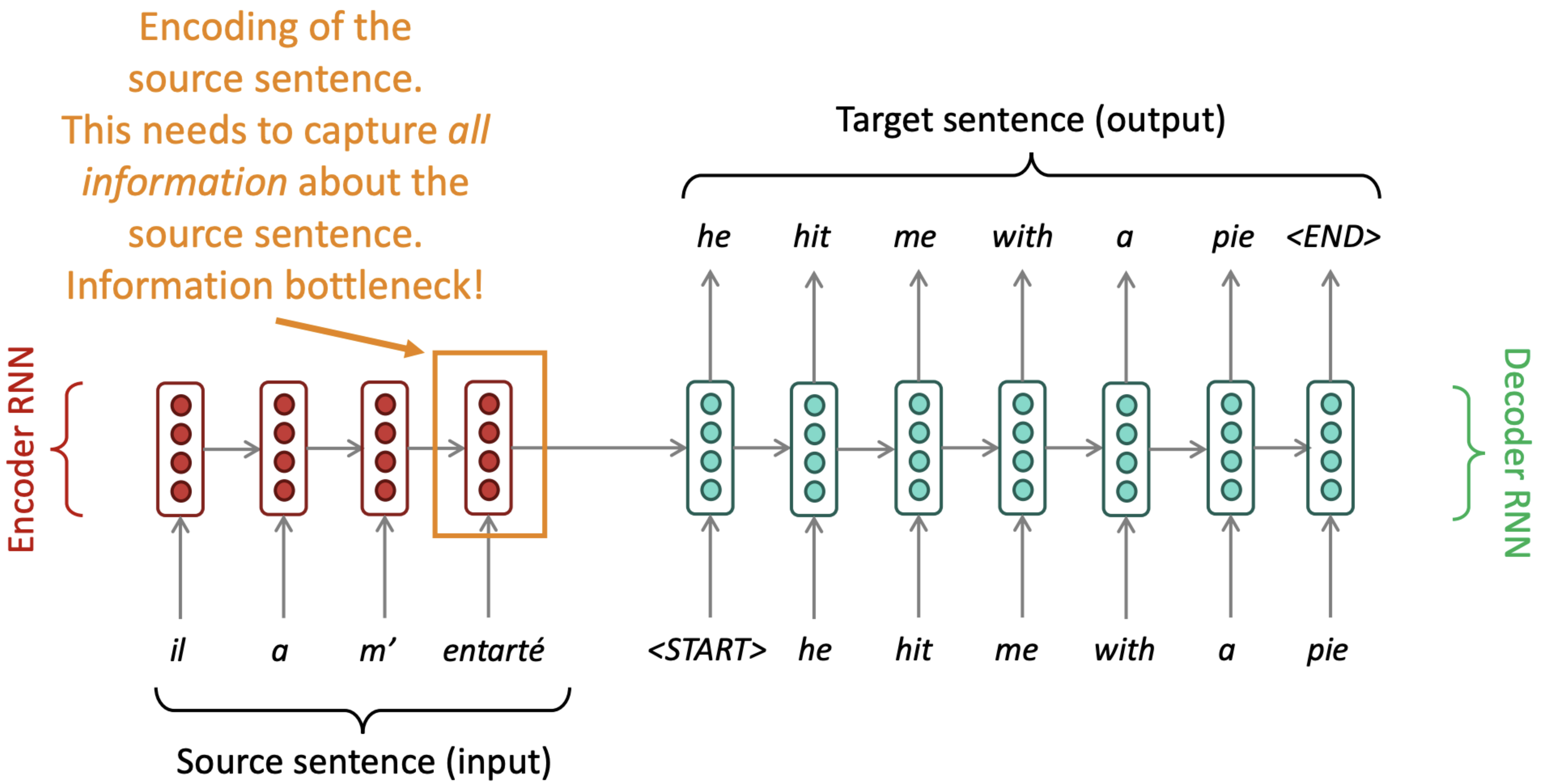


Multi-layer Sequence-to-Sequence

- Multi-layer or stacked RNNs allow the network to compute more complex representations
  - The lower RNNs should compute lower-level features and the higher RNNs should compute higher-level features.
- High-performing RNNs are usually multi-layer (but aren't as deep as convolutional or feed-forward networks)
- For example: In a 2017 paper, Britz et al. find that for Neural Machine Translation, 2 to 4 layers is best for the encoder RNN, and 4 layers is best for the decoder RNN
  - Often 2 layers is a lot better than 1, and 3 might be a little better than 2
  - Usually, skip-connections/dense-connections are needed to train deeper RNNs (e.g., 8 layers)

Sequence-to-Sequence with Attention

Sequence-to-Sequence Bottleneck

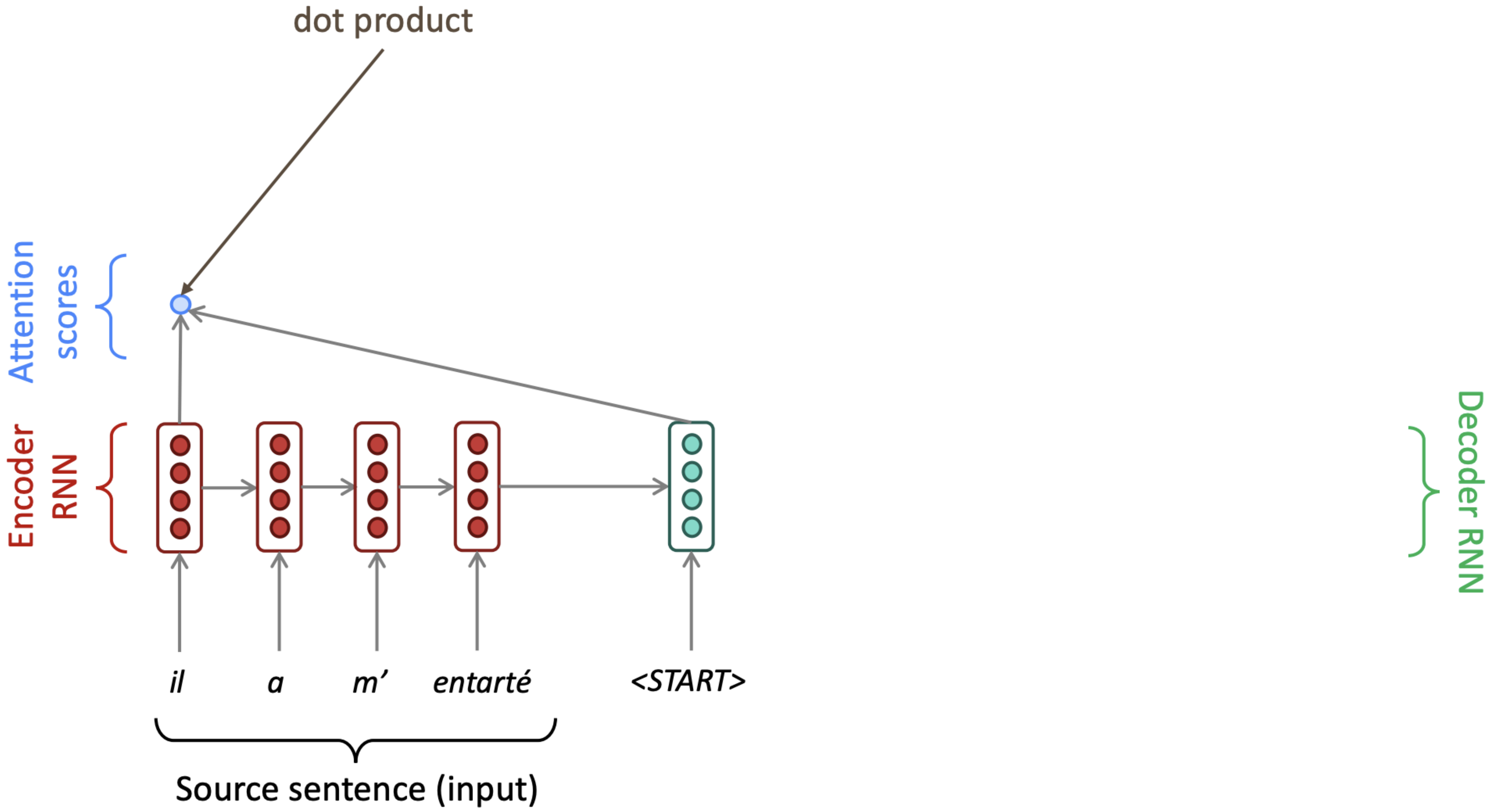


Sequence-to-Sequence with Attention

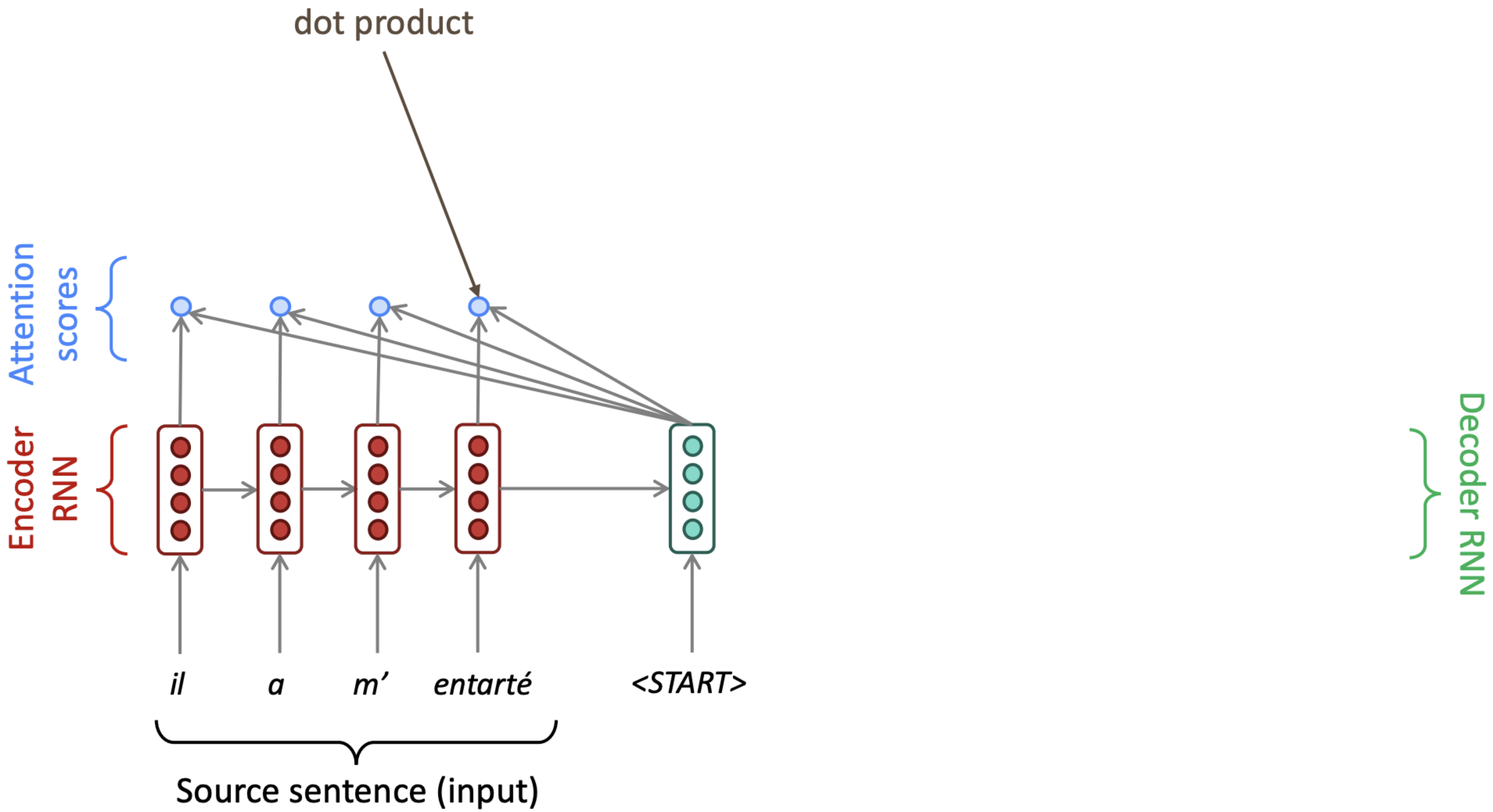
- **Attention** provides a solution to the bottleneck problem.

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

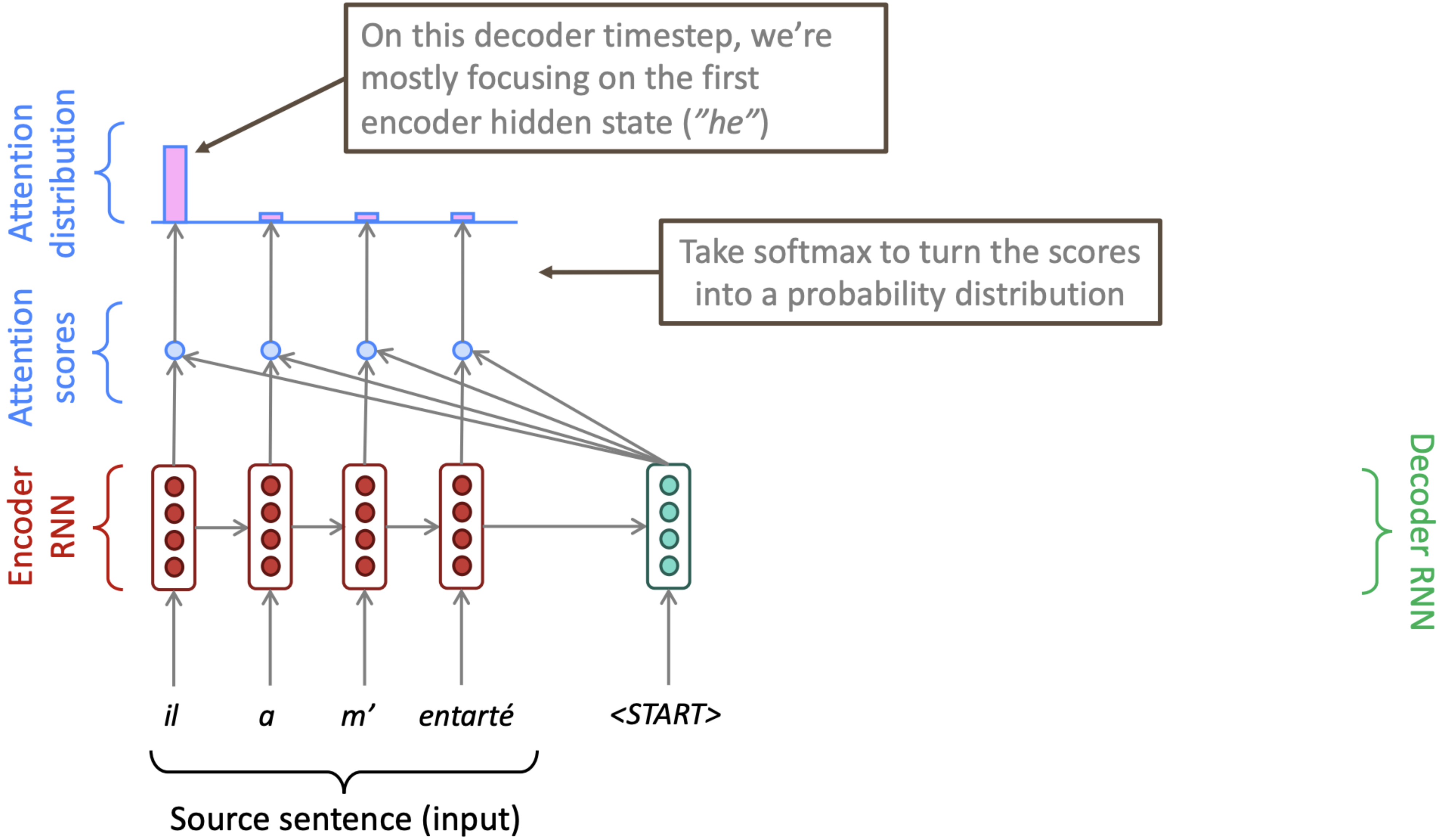
Sequence-to-Sequence with Attention



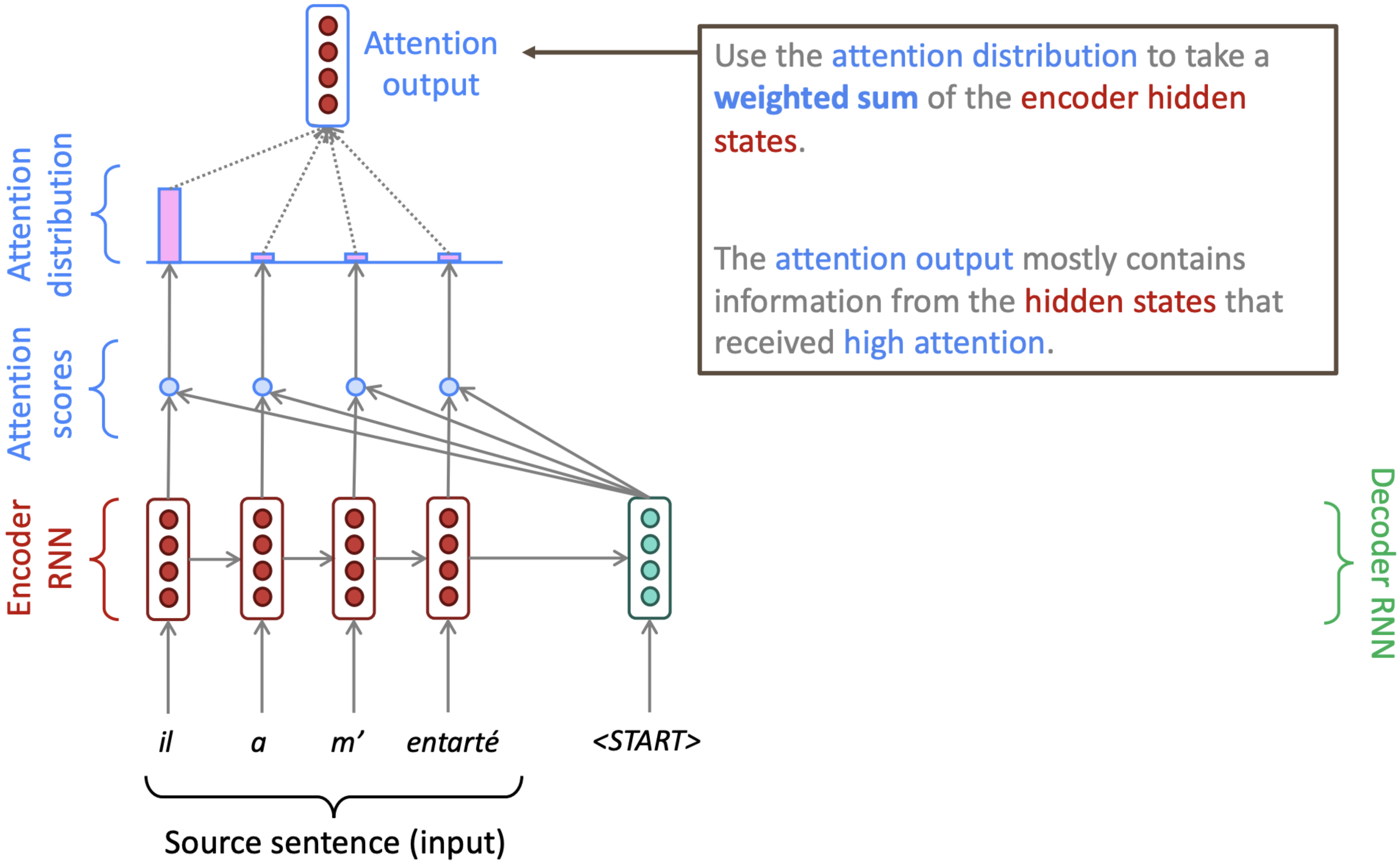
Sequence-to-Sequence with Attention



Sequence-to-Sequence with Attention



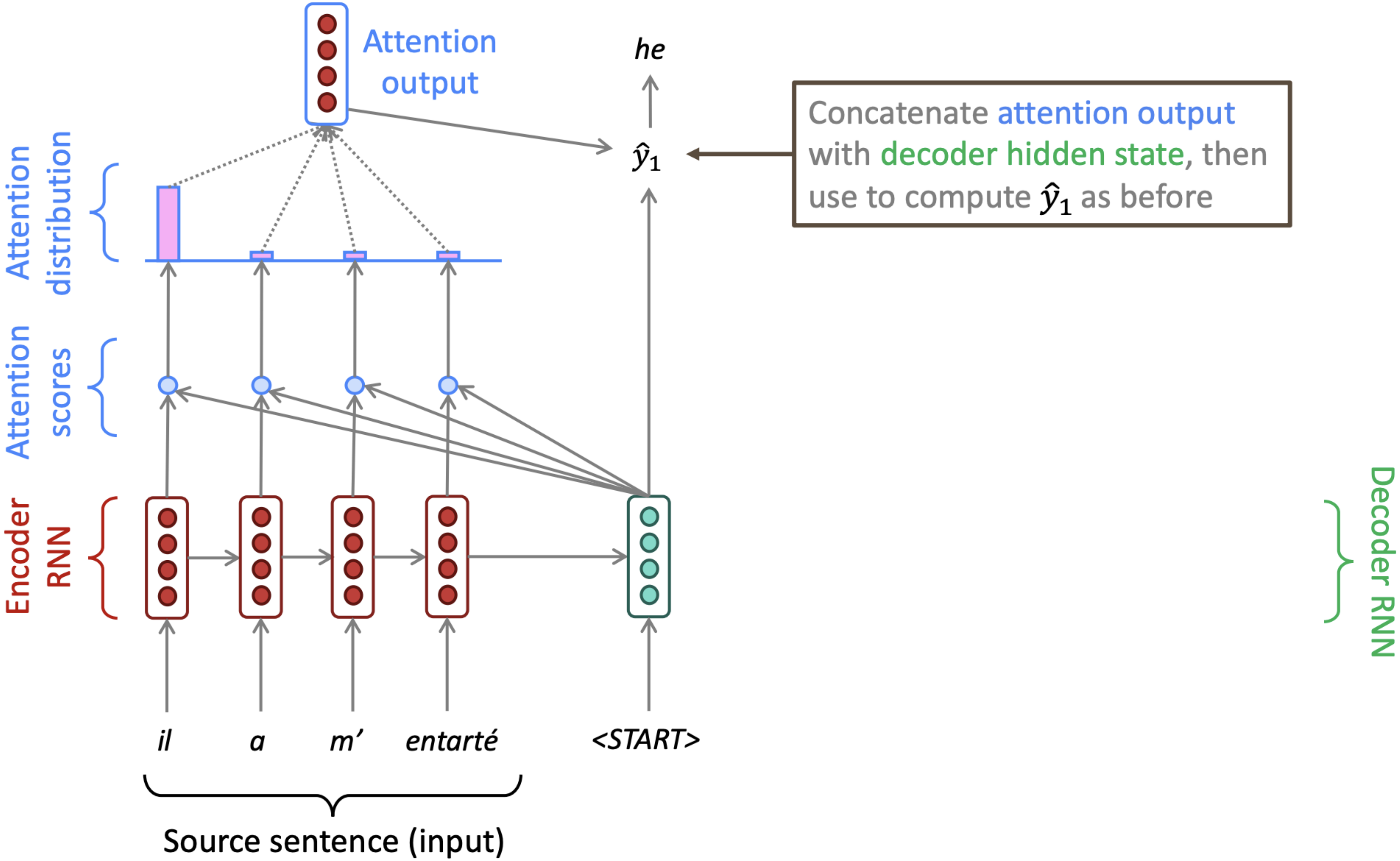
Sequence-to-Sequence with Attention



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

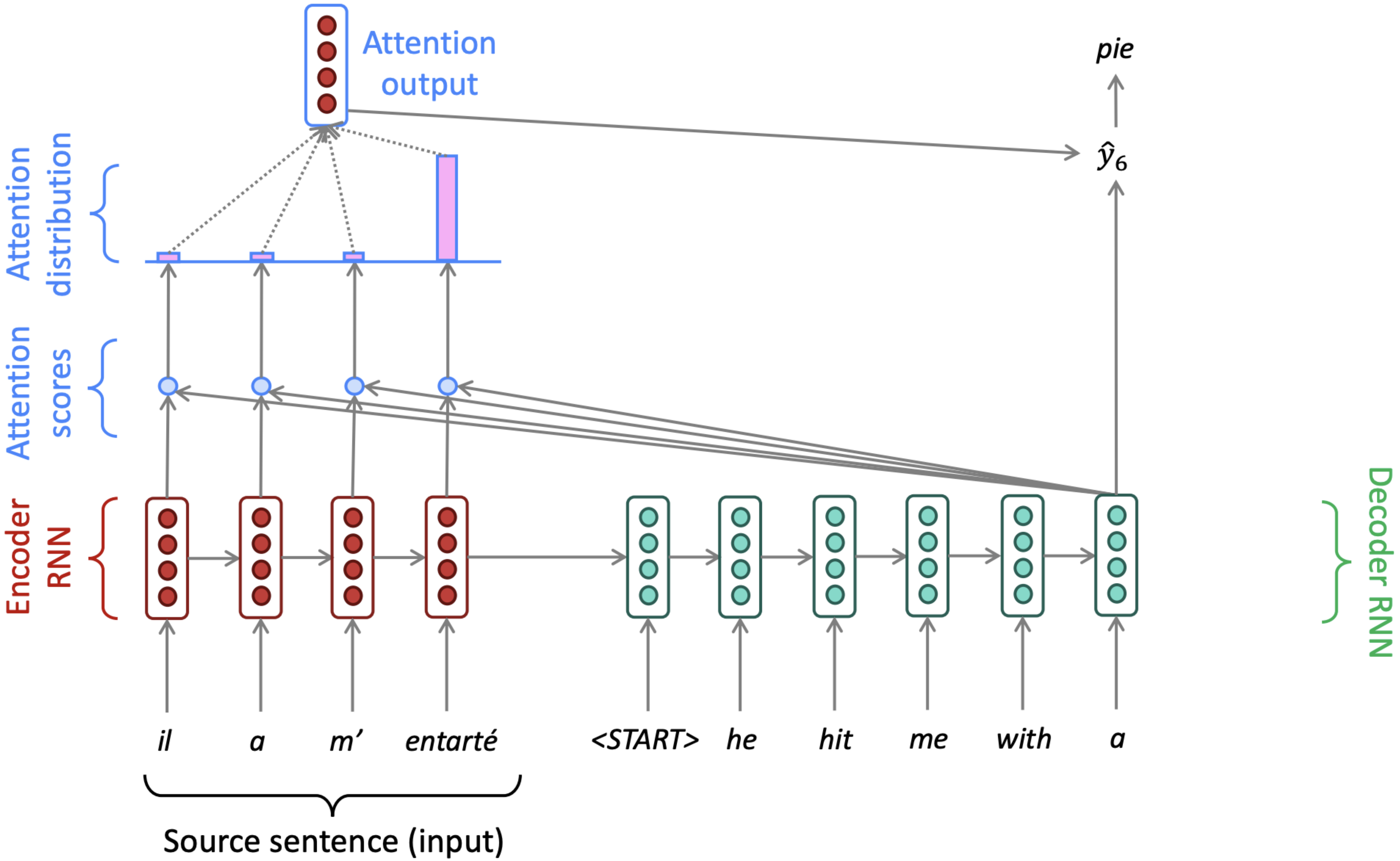
The attention output mostly contains information from the hidden states that received high attention.

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



Sequence-to-Sequence with Attention

- 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

- Attention provides more “human-like” model of the MT process

You can look back at the source sentence while translating, rather than needing to remember it all

- Attention solves the bottleneck problem

Attention allows decoder to look directly at source; bypass bottleneck

- Attention helps with the vanishing gradient problem

Provides shortcut to far-away states

Attention Variants

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

- Attention always involves:
  1. Computing the *attention scores* $\boldsymbol{e} \in \mathbb{R}^N$

     There are multiple ways to do this

  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*)

Attention Variants

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

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

Attention is a general concept

- You can use attention in many architectures and many tasks
- 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 concept

- 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).

Thank you!

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