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Natural Language Processing

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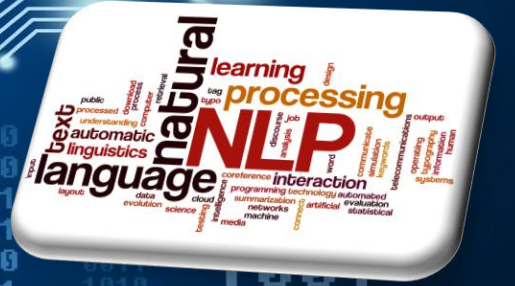


Machine Translation

- It is the use of computers to translate from one language to another.

- Machine translation (MT) focuses on a number of very **practical tasks**:
  - **Information access:** translate information on the web such as articles, reviews, …
  - **Computer-aided translation (CAT):** produce a draft translation that is fixed up in a post-editing phase by a human translator.
  - **In-the-moment human communication needs:** incremental translation, translating speech on-the-fly before the entire sentence is complete.
  - **Image-centric translation:** use OCR of the text on a phone camera image as input to an MT system to translate menus or street signs.

- The standard algorithm for MT is the **encoder-decoder network**, also called the **sequence to sequence network**, an architecture that can be implemented with RNNs or with Transformers.

Machine Translation

- Encoder-decoder or sequence-to-sequence models are used for a different kind of sequence modeling (either than POS-tagging/NER) in which the output sequence is a complex function of the entire input sequencer

  →mapping from a sequence of input words or tokens to a sequence of tags that are **not merely direct mappings from individual words**.

- Example:

English:	*He wrote a letter to a friend*		
Japanese:	*tomodachi ni tegami-o kaita*		
	friend	to letter	wrote

  - In English, the verb is in the middle of the sentence, while in Japanese, the verb *kaita* comes at the end. The Japanese sentence doesn't require the pronoun *he*, while English does.

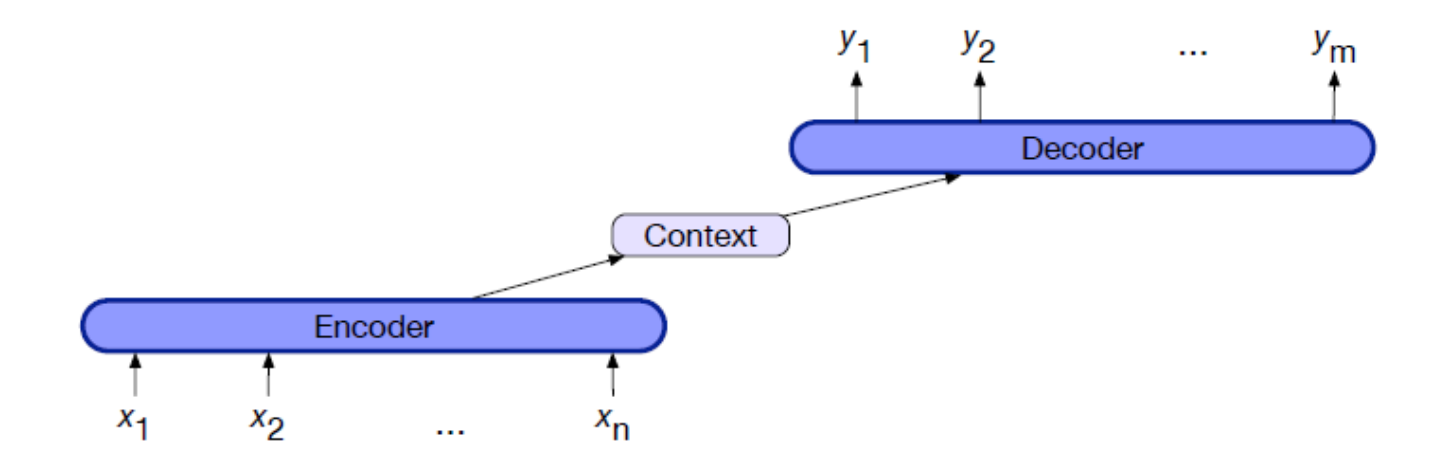
- Encoder-decoder networks are very successful at handling these sorts of complicated cases of sequence mappings.
- The encoder-decoder algorithm is not just for MT, it's the state of the art for many other tasks where complex mappings between two sequences are involved:
  - **summarization** (where we map from a long text to its summary, like a title or an abstract)
  - **dialogue** (where we map from what the user said to what our dialogue system should respond)
  - **semantic parsing** (where we map from a string of words to a semantic representation like logic or SQL).

Encoder-Decoder Model

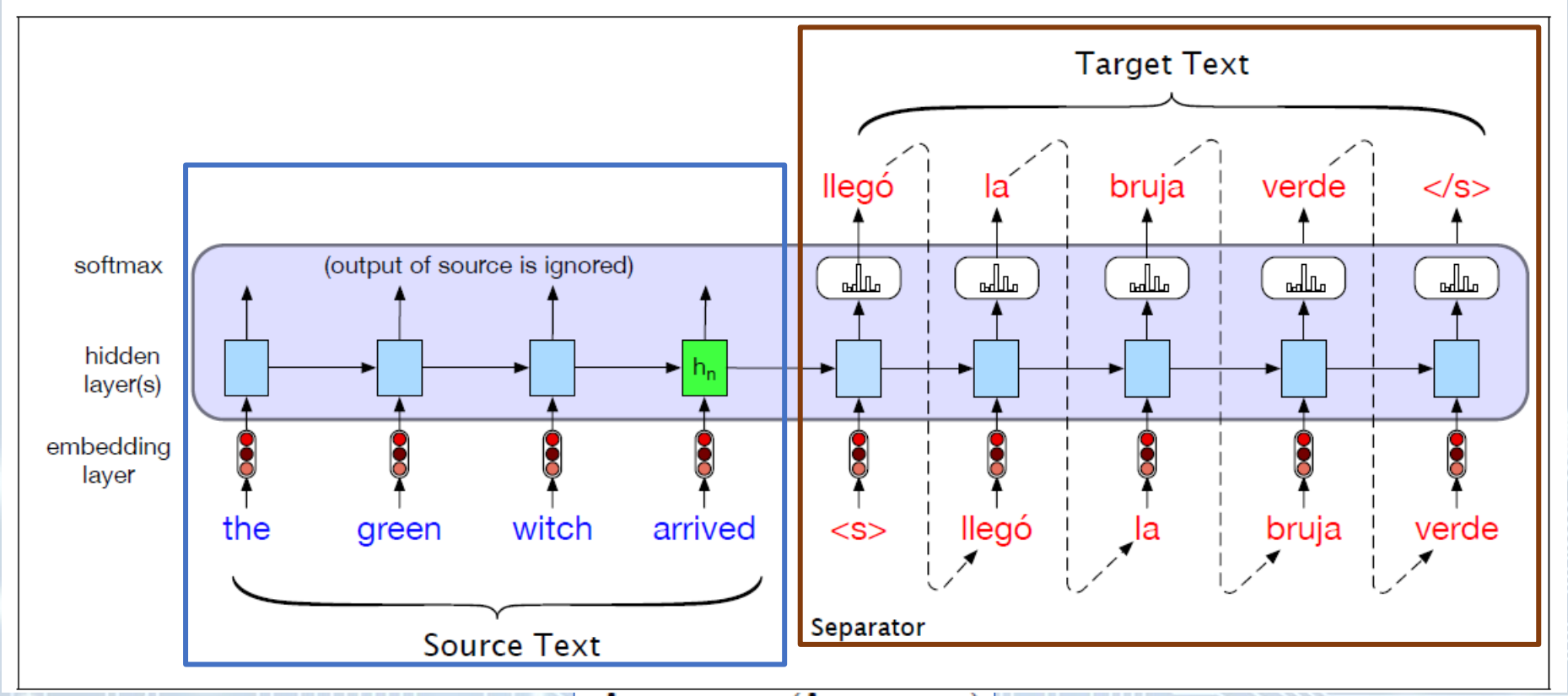
- Are models capable of generating contextually appropriate, **arbitrary length**, output sequences.

- Applied to a very wide range of applications including machine translation, summarization, question answering, and dialogue.

- The key idea: is the use of an **encoder** network that takes an input sequence and creates a contextualized representation of it, often called the **context**. This representation is then passed to a **decoder** which generates a task-specific output sequence.



Encoder-Decoder with RNNs



$$\mathbf{h}_t = g(\mathbf{h}_{t-1}, \mathbf{x}_t)$$
$$\mathbf{y}_t = f(\mathbf{h}_t)$$

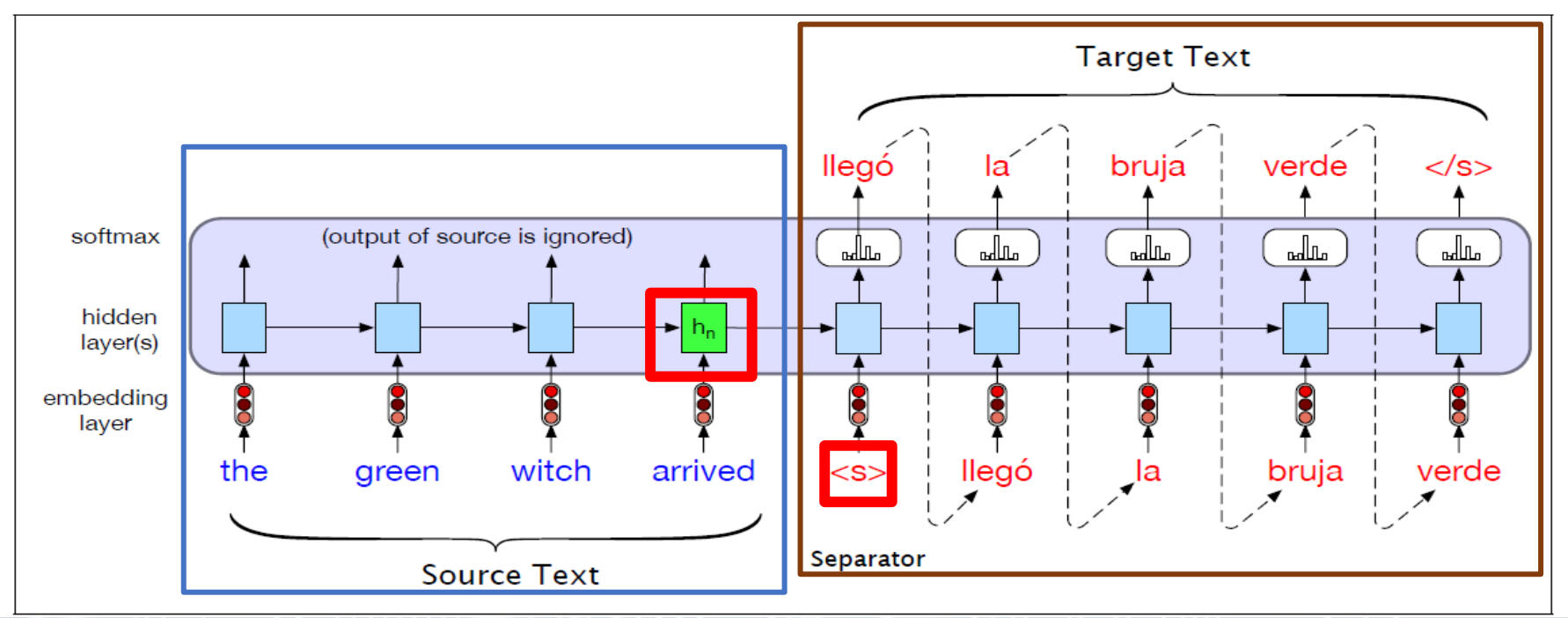
- g is an activation function like **tanh** or **ReLU**, a function of the input at time t and the hidden state at time t-1.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad f(x) = \max(0, x)$$

- f is a softmax over the set of possible vocabulary items.

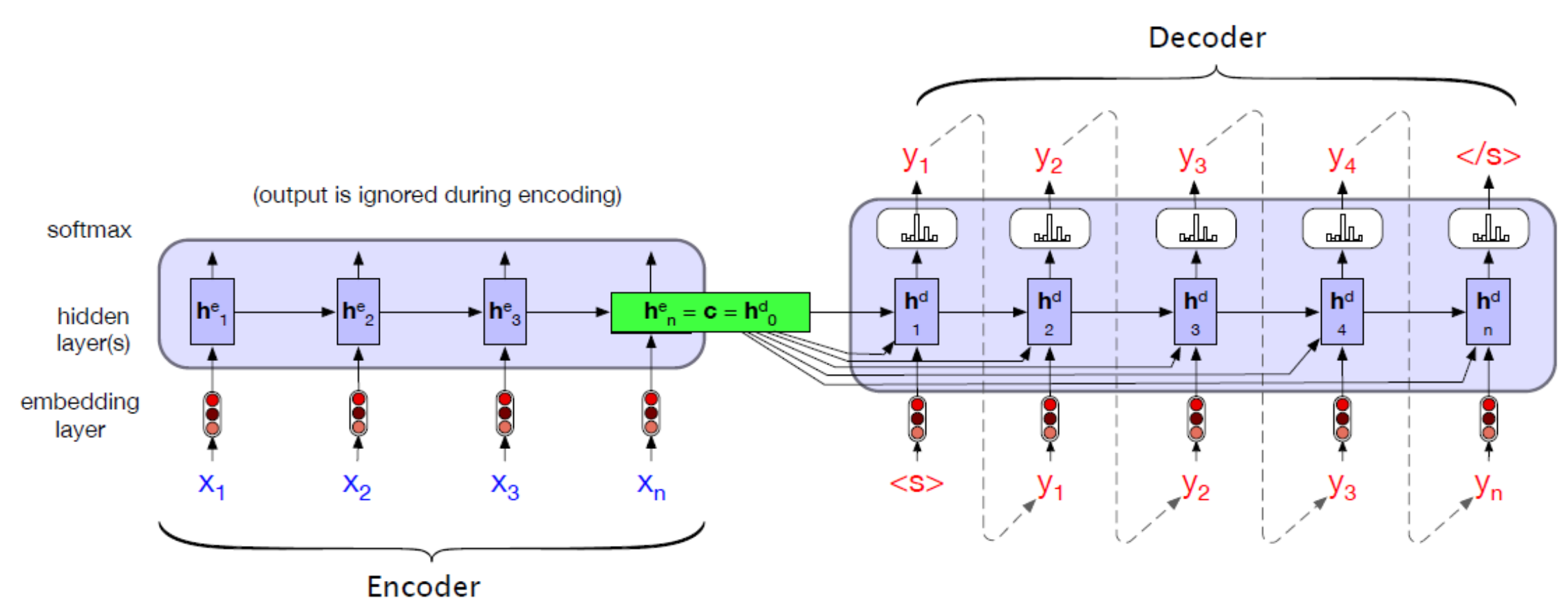
Encoder-Decoder with RNNs

- In MT, note the addition of a **sentence separation marker** at the end of the source text, and then simply concatenate the target text.



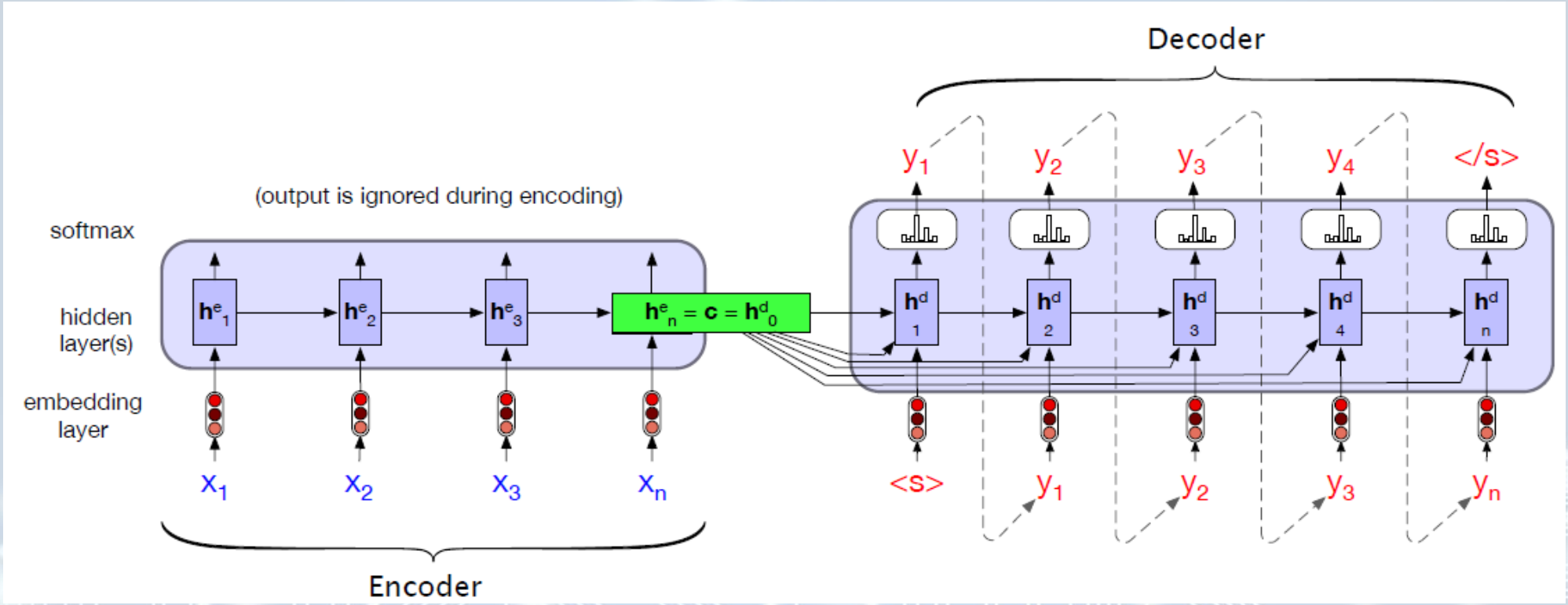
- An English source text (“the green witch arrived”), a sentence separator token <s>, and a Spanish target text (“llego´ la bruja verde”).
- To translate a source text, we run it through the network performing forward inference to generate hidden states until we get to the end of the source “hn”. Then we begin **autoregressive generation**, asking for a word in the context of the hidden layer from the end of the source input.
- Subsequent words are conditioned on the previous hidden state and the embedding for the last word generated.

Encoder-Decoder with RNNs



- The elements of the network on the left process the input sequence x and comprise the **encoder**.
- While our simplified figure shows only a single network layer for the encoder, stacked architectures are the norm, where the output states from the top layer of the stack are taken as the final representation.

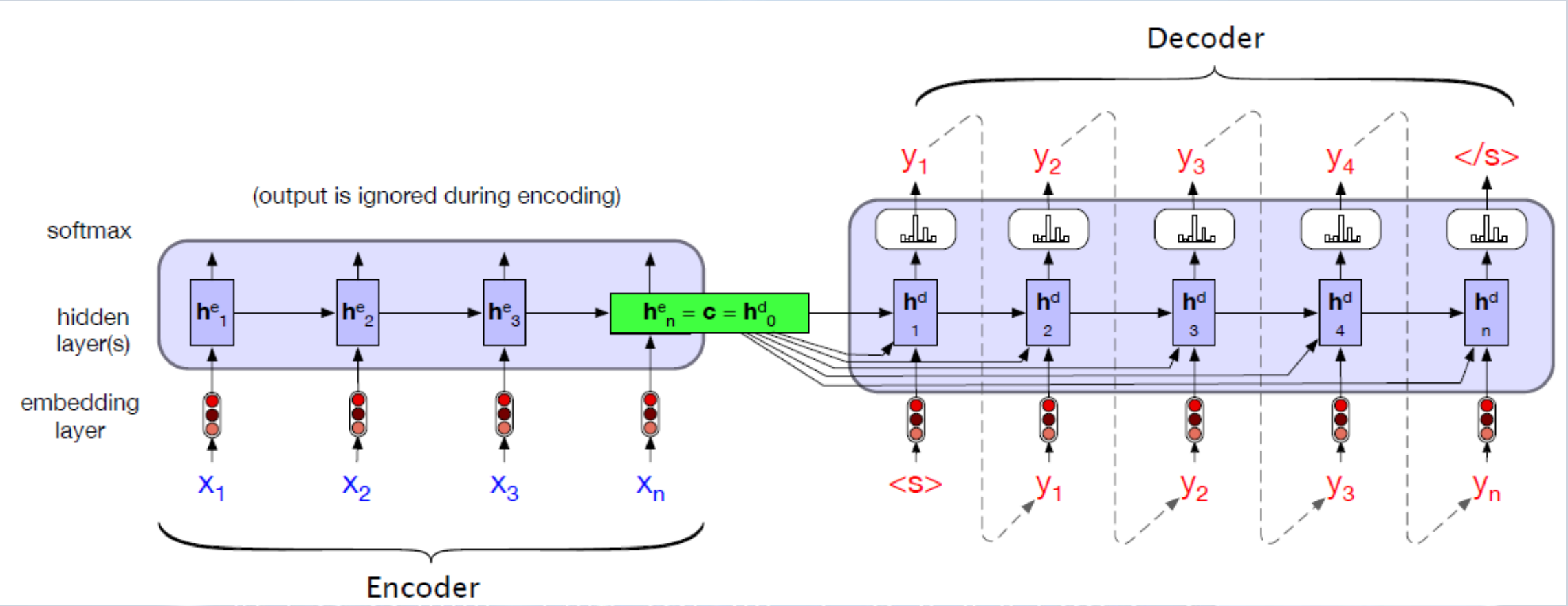
Encoder-Decoder with RNNs



- The entire purpose of the encoder is to generate a contextualized representation of the input. This representation is embodied in the final hidden state of the encoder h^e_n called ***c*** for **context**, is then passed to the decoder.

- The **decoder** network on the right takes this state and uses it to initialize the first hidden state of the decoder. That is, the first decoder RNN cell uses c as its prior hidden state h^d_0 .

Encoder-Decoder with RNNs



- The decoder autoregressively generates a sequence of outputs, an element at a time, until an **end-of-sequence marker** is generated.

- Each hidden state is conditioned on the previous hidden state and the output generated in the previous state.

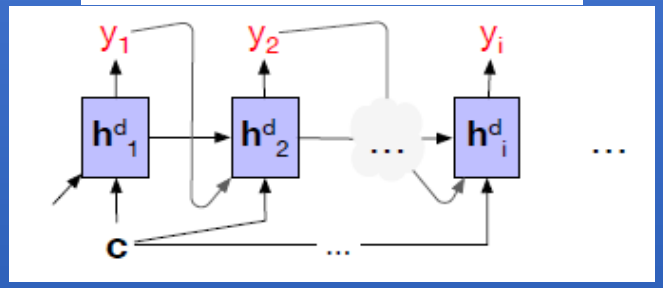
Encoder-Decoder with RNNs

- One weakness of this approach as described so far is that the influence of the context vector c will decrease as the output sequence is generated.

Solution:

Make the context vector **c** available at each step in the decoding process by adding it as a parameter to the computation of the current hidden state:

$$\mathbf{h}_t^d = g(\hat{y}_{t-1}, \mathbf{h}_{t-1}^d, \mathbf{c})$$



- Full equations for this version of the decoder in the basic encoder-decoder model:

$$\begin{aligned}
\mathbf{c} &= \mathbf{h}_n^e \\
\mathbf{h}_0^d &= \mathbf{c} \\
\mathbf{h}_t^d &= g(\hat{y}_{t-1}, \mathbf{h}_{t-1}^d, \mathbf{c}) \\
\mathbf{z}_t &= f(\mathbf{h}_t^d) \\
y_t &= \text{softmax}(\mathbf{z}_t)
\end{aligned}$$

Incase of multiple layers

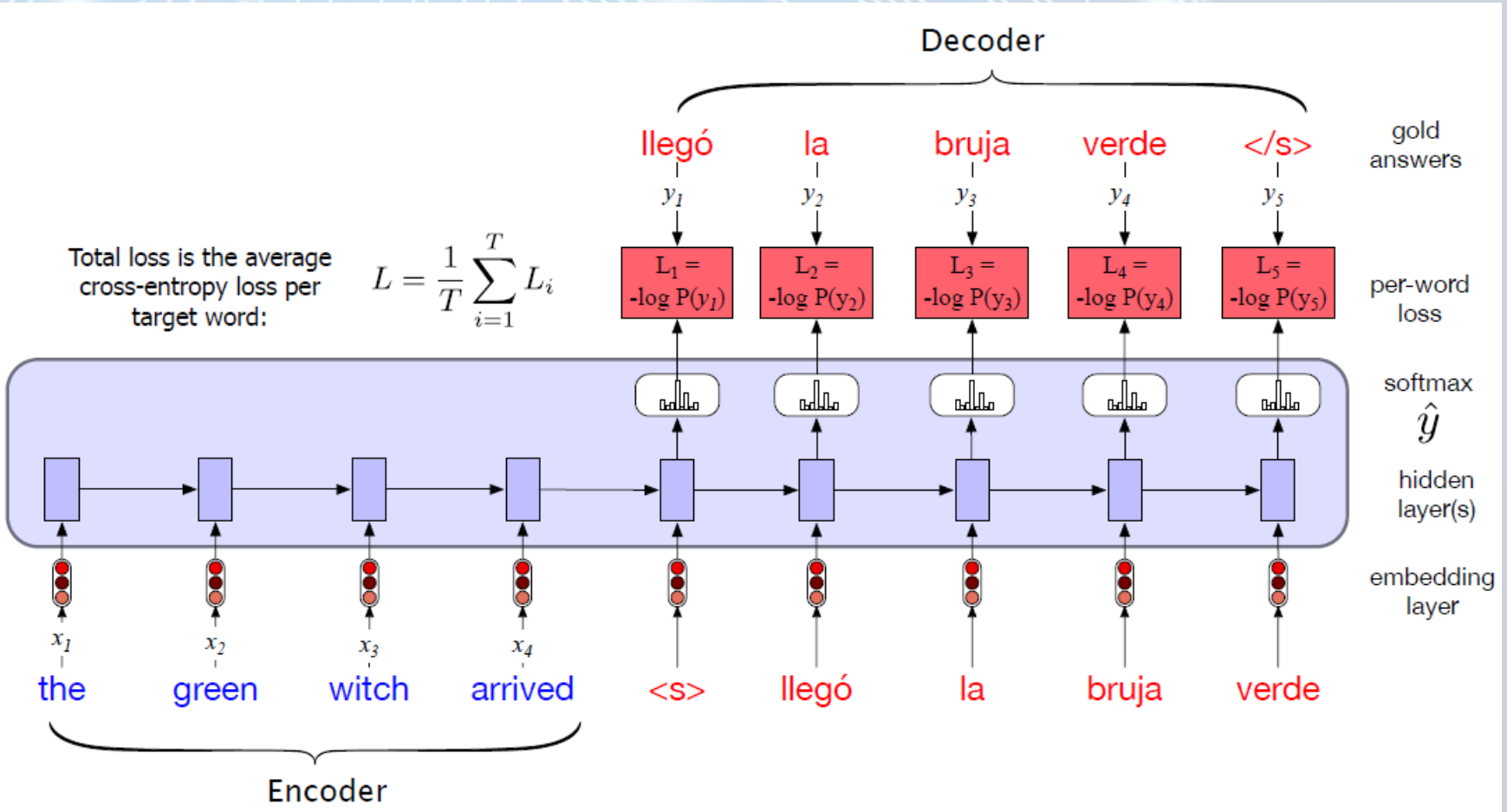
is the embedding for the output sampled from the softmax at the previous step

Training the Encoder-Decoder Model

- Each training example is a tuple of paired strings, a source and a target.
- Concatenated with a separator token, these source-target pairs serve as training data.
- The training itself proceeds as with any RNN-based language model.
- The network is given the source text and then starting with the separator token is trained autoregressively to predict the next word.

In the decoder:

- **During inference:** it uses its own estimated output $\hat{y}_t$ as the input for the next time step x_{t+1}.
- **During Training:** we usually don't propagate the model's softmax outputs, but use **teacher forcing** to force each input to the correct gold value→ this speeds up training. We compute the softmax output distribution over $\hat{y}_t$ to compute the loss at each token.



Attention

- The simplicity of the encoder-decoder model is its clean separation of the encoder—which builds a representation of the source text—from the decoder, which uses this context to generate a target text.

  →this context vector is ***hn***, the hidden state of the last (nth) time step of the source text.

- This final hidden state is thus acting as a **bottleneck**: it must represent absolutely everything about the meaning of the source text, since the only thing the decoder knows about the source text is what's in this context vector.

- Information at the beginning of the sentence, especially for long sentences, may not be equally well represented in the context vector.

Solution:

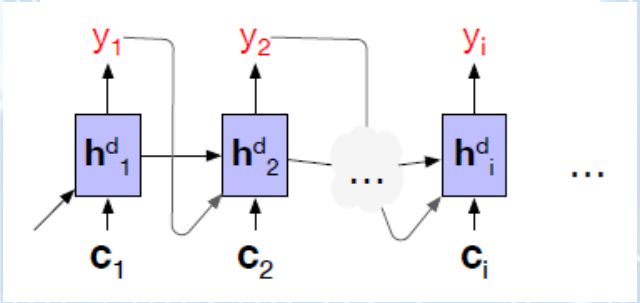
attention mechanism a way of mechanism allowing the decoder to get information from all the hidden states of the encoder, not just the last hidden state.

Attention

- Create a **fixed-length** vector c by taking a **weighted sum** of all the encoder hidden states.
- The weights focus on ('attend to') a particular part of the source text that is relevant for the token the decoder is currently producing.

Attention thus replaces the static context vector with one that is **dynamic**, different for each token in decoding

$$\mathbf{h}_i^d = g(\hat{y}_{i-1}, \mathbf{h}_{i-1}^d, \mathbf{c}_i)$$



- The first step in computing c_i is to compute how much to focus on each encoder state →how relevant each encoder state is to the decoder state captured in h_{i-1}^d

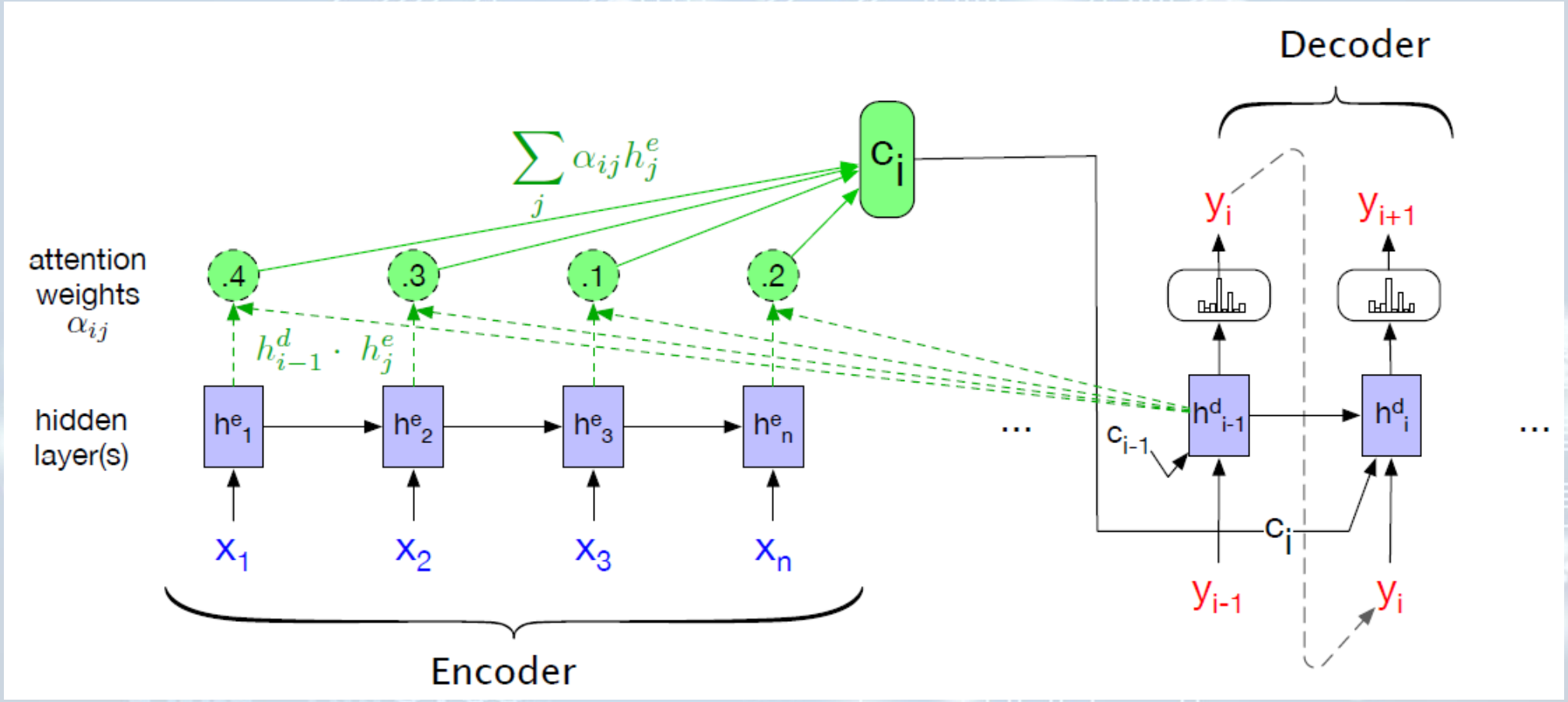
Attention

- To capture relevance: at each state *i* during decoding a score for each encoder state *j* is computed $\boldsymbol{score}\left(\boldsymbol{h}_{\boldsymbol{i-1}}^{\boldsymbol{d}}, \boldsymbol{h}_{\boldsymbol{j}}^{\boldsymbol{e}}\right)$
- The simplest such score **"dot-product attention"** $$score(\mathbf{h}_{i-1}^{d}, \mathbf{h}_{j}^{e}) = \mathbf{h}_{i-1}^{d} \cdot \mathbf{h}_{j}^{e}$$
- The score that results from this dot product is a scalar that reflects the degree of similarity between the two vectors.
- The vector of these scores across all the encoder hidden states gives us the relevance of each encoder state to the current step of the decoder.
- We normalize these scores with a softmax to create a vector of weights α_{ij}, that tells us the **proportional relevance** of each encoder hidden state *j* to the prior hidden decoder state h_{i-1}^{d} .

$$\begin{aligned}\alpha_{ij} &= \text{softmax}(score(\mathbf{h}_{i-1}^{d}, \mathbf{h}_{j}^{e}) \;\; \forall j \in e) \\ &= \frac{\exp(score(\mathbf{h}_{i-1}^{d}, \mathbf{h}_{j}^{e})}{\sum_{k} \exp(score(\mathbf{h}_{i-1}^{d}, \mathbf{h}_{k}^{e}))}\end{aligned}$$

Attention

- The context vector for the current decoder state: $\mathbf{c}_i = \sum_j \alpha_{ij}\, \mathbf{h}_j^e$



Note: the encoder and decoder hidden states must have the same dimensionality.

Note

- The described decoding is **greedy:** at each time step in decoding, the output y_t is chosen by computing a softmax over the set of possible outputs (the vocabulary, in the case of language modeling or MT), and then choosing the **highest probability token** → the choice is **locally optimal**

- Greedy search is not optimal, and may not find the highest probability translation →the problem is that the token that looks good to the decoder now might turn out later to have been the wrong choice!

- Another generally used decoding method in MT is called **beam search**. In beam search, instead of choosing the best token to generate at each timestep, we keep *k* possible tokens at each step.


Thank You