# Attention in NLP

CS 6956: Deep Learning for NLP

THE UNIVERSITY OF UTAH

# Overview

- What is attention
- Attention in encoder-decoder networks
- Various kinds of attention

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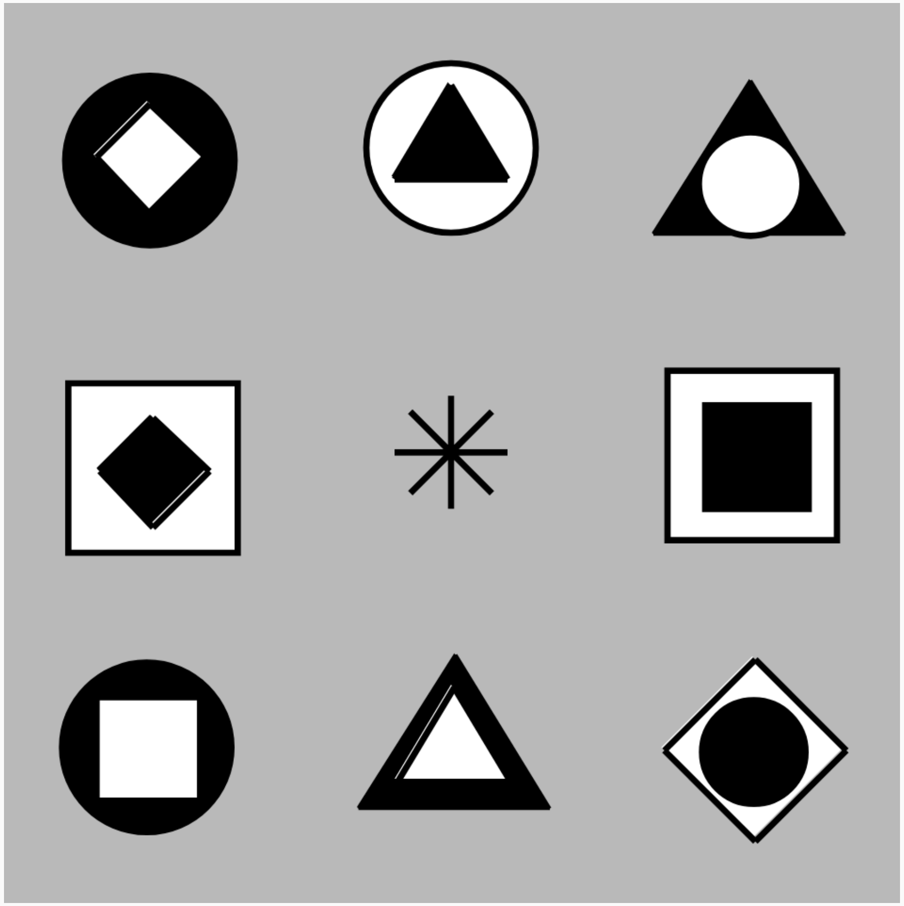
- What is attention?
- Attention in encoder-decoder networks

# Visual attention



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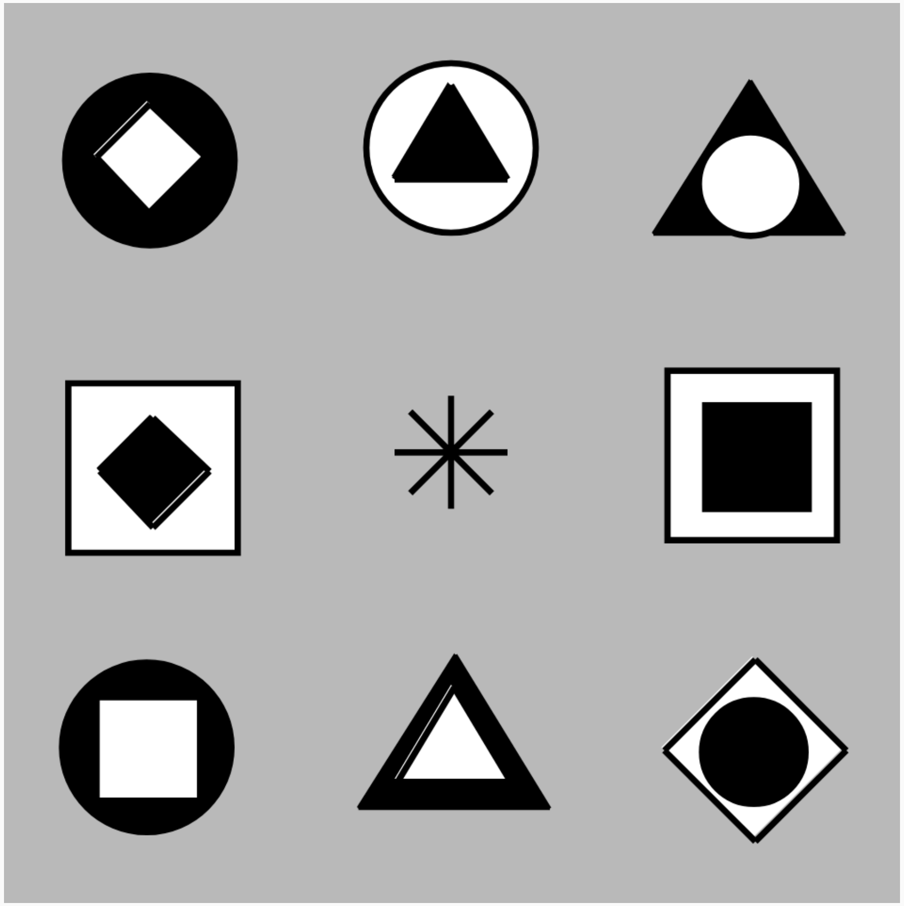

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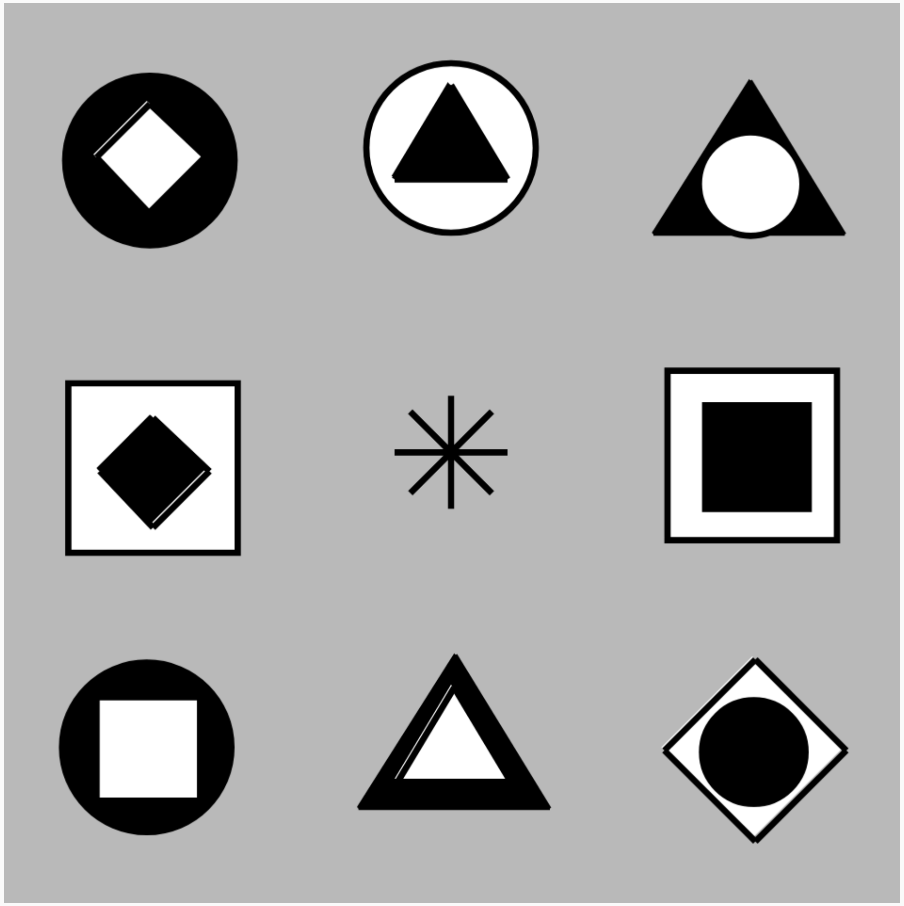

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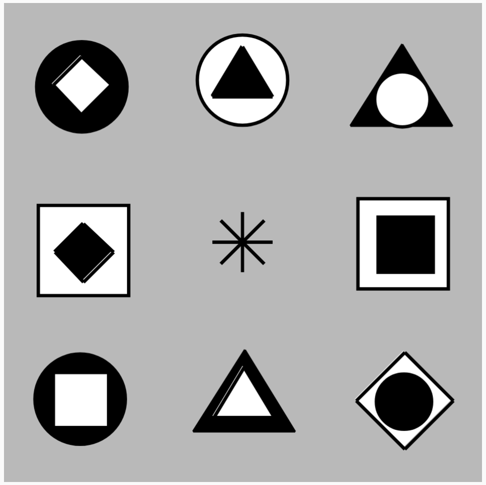

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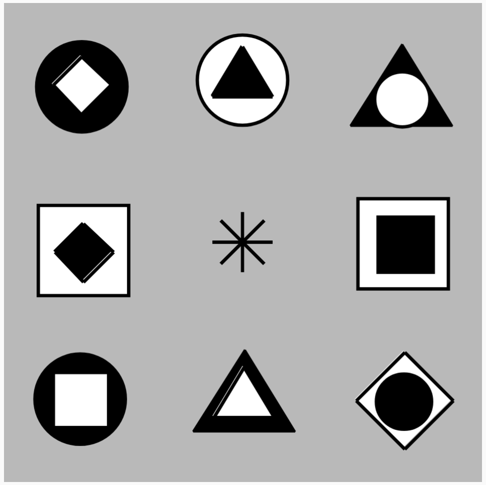

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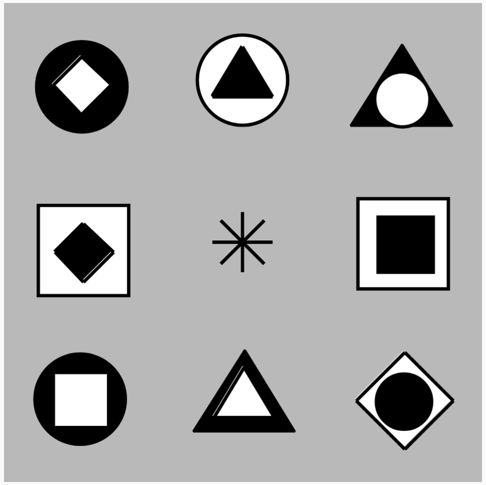

To answer the questions, you needed to check one object at a time.

If you were looking at the center of the image to answer the questions, then you internally changed how to process the input without the input changing

In other words, you exercised your ***visual attention***

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# What is attention?

- All inputs may not need careful processing at all points of time

- Attention: A mechanism for selecting a subset of information for further analysis/processing/computation
  - *Focus* on the most relevant information, and ignore the rest

- Widely studied in cognitive psychology, neuroscience and related fields
  - Often seen in the context of visual information

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- Generally it takes the following form:
  – We have a large input, but need to focus on only a small part
  – An auxiliary network predicts a distribution over the input that decides the attention over its parts
  – The output is the weighted sum of the attention and the input

# Example application: Machine Translation

Suppose we have to convert a Dutch sentence into its English translation

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↓

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This requires us to consume a sequence and generate a new one that means the same

# Consuming and generating sequences

Recurrent neural networks as general sequence processors

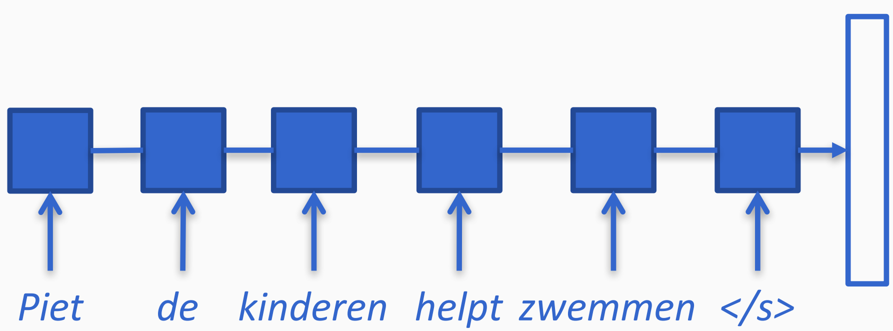
- RNNs can encode a sequence into sequence of state vectors
- RNNs can generate sequences starting with an initial input
  - And can even take inputs at each step to guide the generation

# The encoder-decoder approach

[Sutskever, et al 2014, Cho et al 2014]

Encode the input using an RNN till a special end-of-input token is reached

(Could be a bi-directional RNN)



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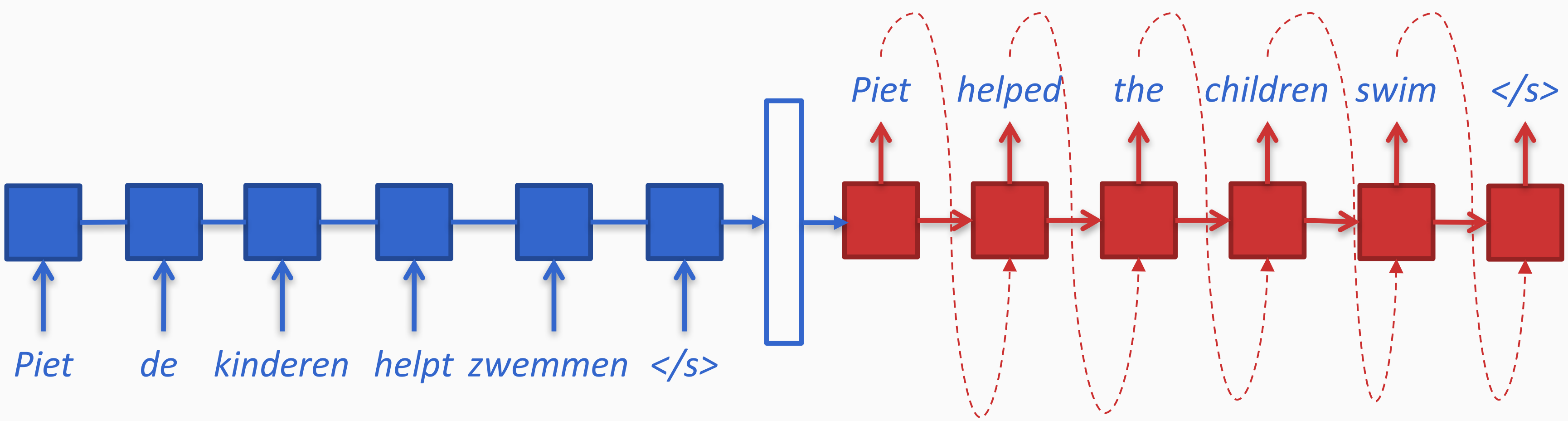

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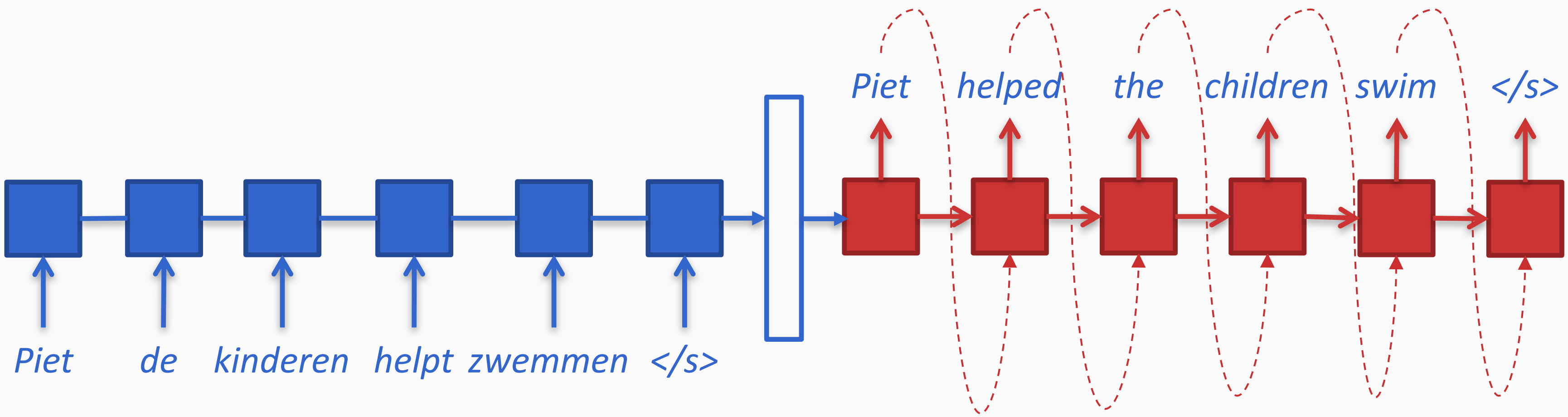
The decoder produces probabilities over the output sequence words



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In practice: such a simple encoder-decoder network works for short sentences (10-15 words)

Needs other modeling refinements to improve beyond this

# Adding attention to the decoder

[Bahdanau, 2014]

- Deciding on each output word does not depend on *all* input words
- Instead, if we can dynamically attend over the inputs for each output, then the decision of which output word to generate could be more targeted
- Let's build such a model from scratch

# Step 1: The encoder

- Input sequence of words: $x_1, x_2, \cdots$
  - Assume that the we have special start and end tokens

- Bidirectional RNN (usually LSTM) encodes the sequence to produce a sequence of hidden states

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Concatenated states from the left and right RNNs

# Step 2: The decoder

- Suppose the output words are $y_1, y_2, \cdots$
- For the $i^{th}$ output word, suppose we summarize the input into a vector $\mathbf{c}_i$
  - We will look at what this vector is very soon
- The probability of $i^{th}$ output word depends on
  - The previous word generated $y_{i-1}$
  - The hidden state of the decoder, say $\mathbf{s}_{i-1}$
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$$\text{softmax}(W_o y_{i-1} + W_h \mathbf{s}_{i-1} + W_c \mathbf{c}_i + b)$$

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The previous word is represented by its embedding

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Probability over all the target words

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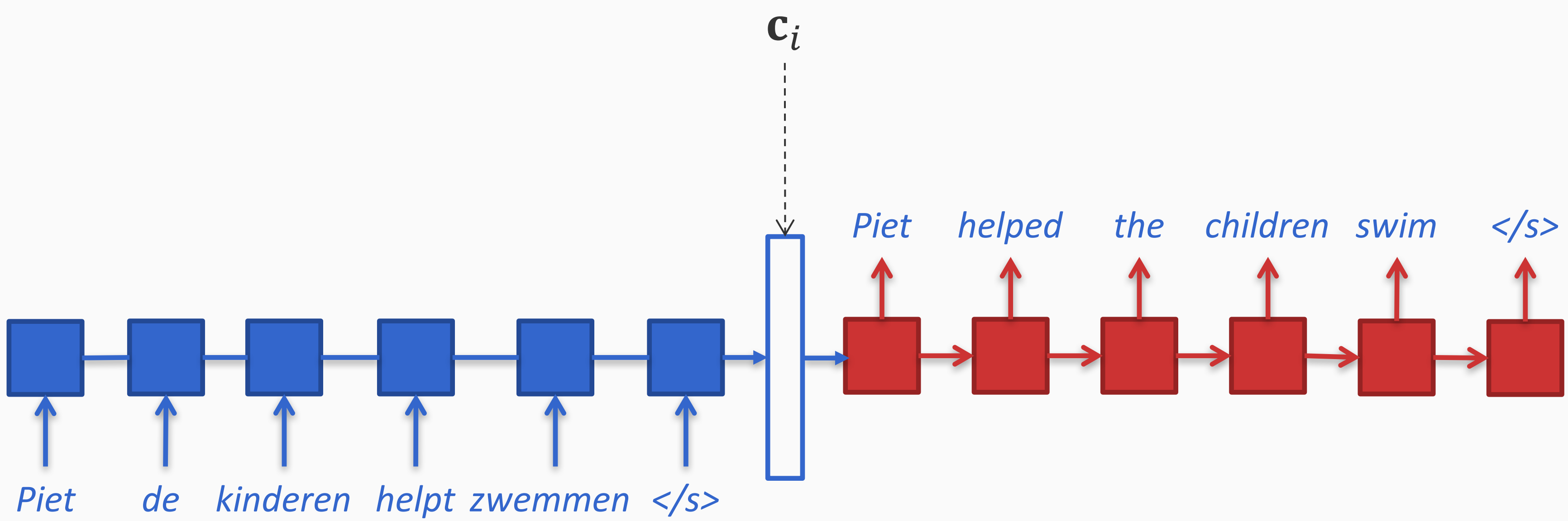
At the $i^{th}$ step, the vector $\mathbf{c}_i$ should highlight information about the input words that is being translated



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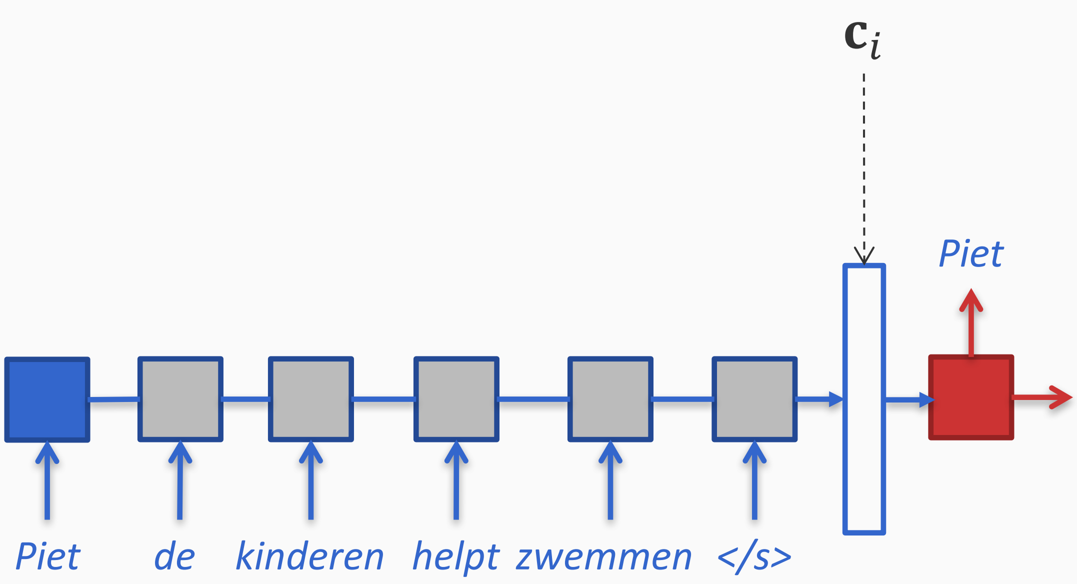

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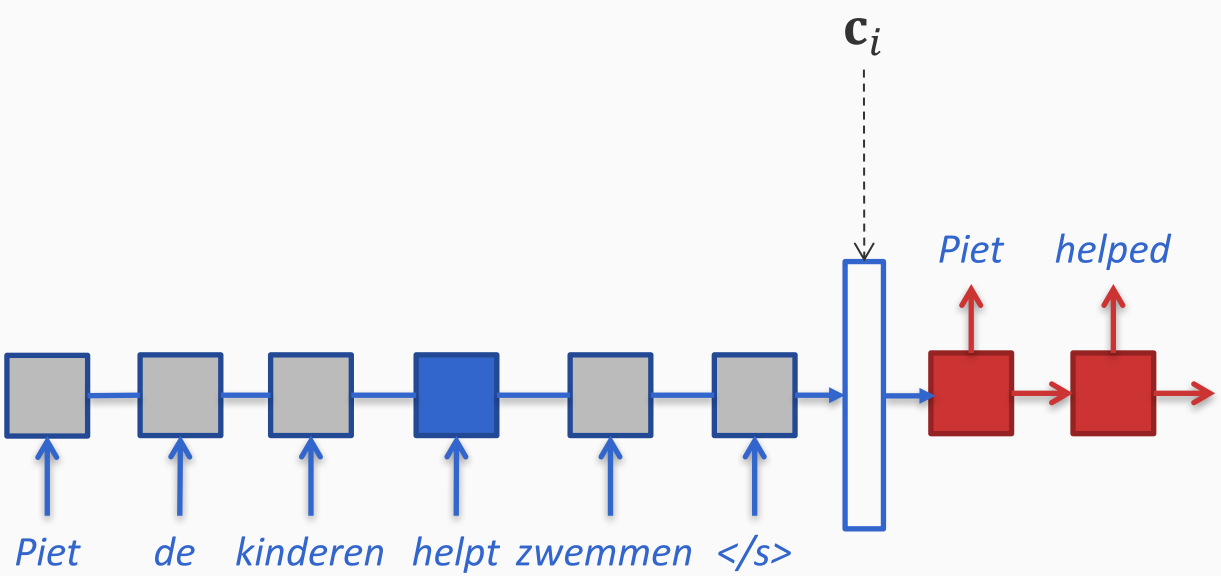

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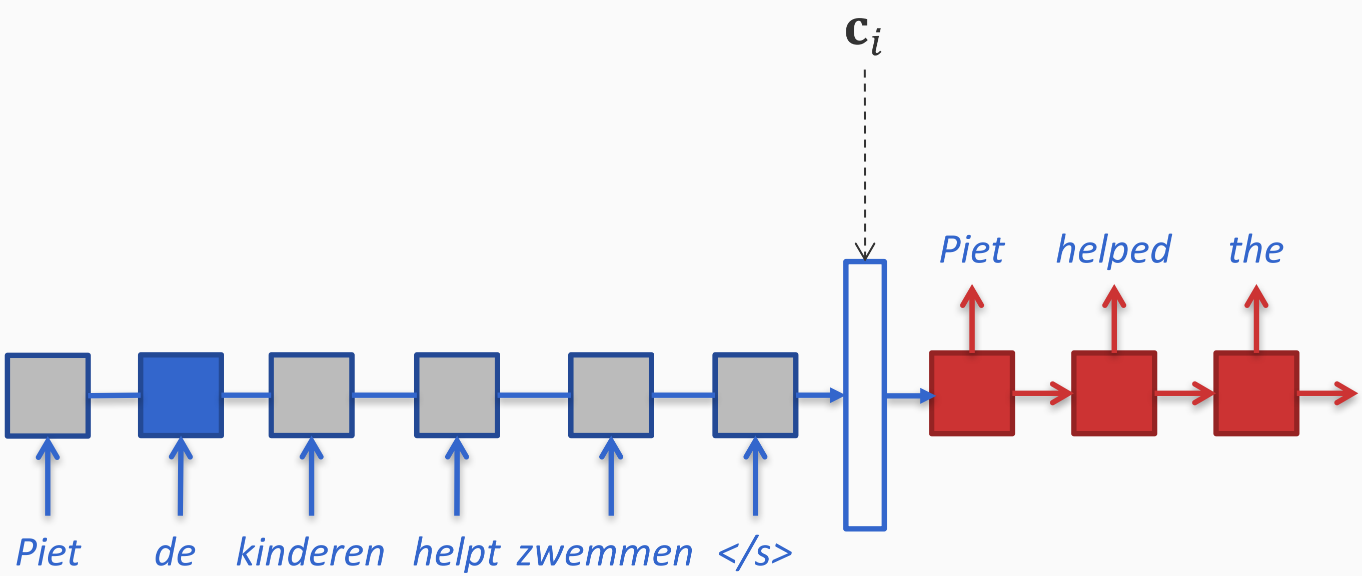

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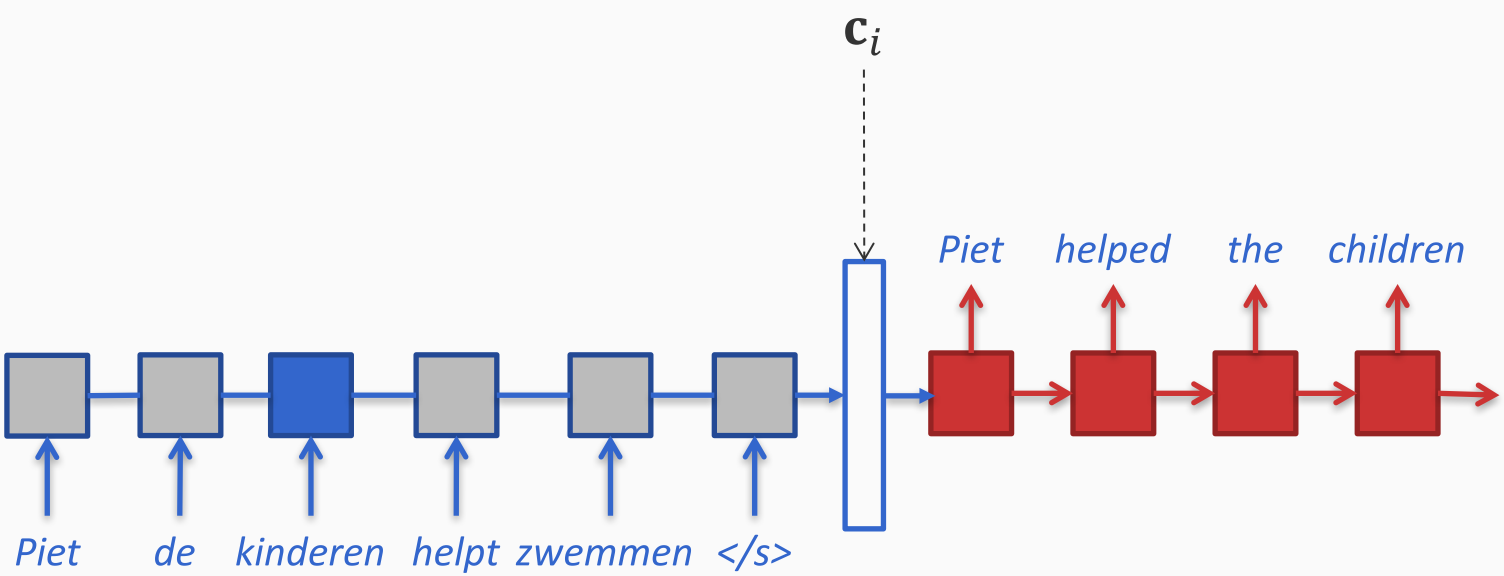

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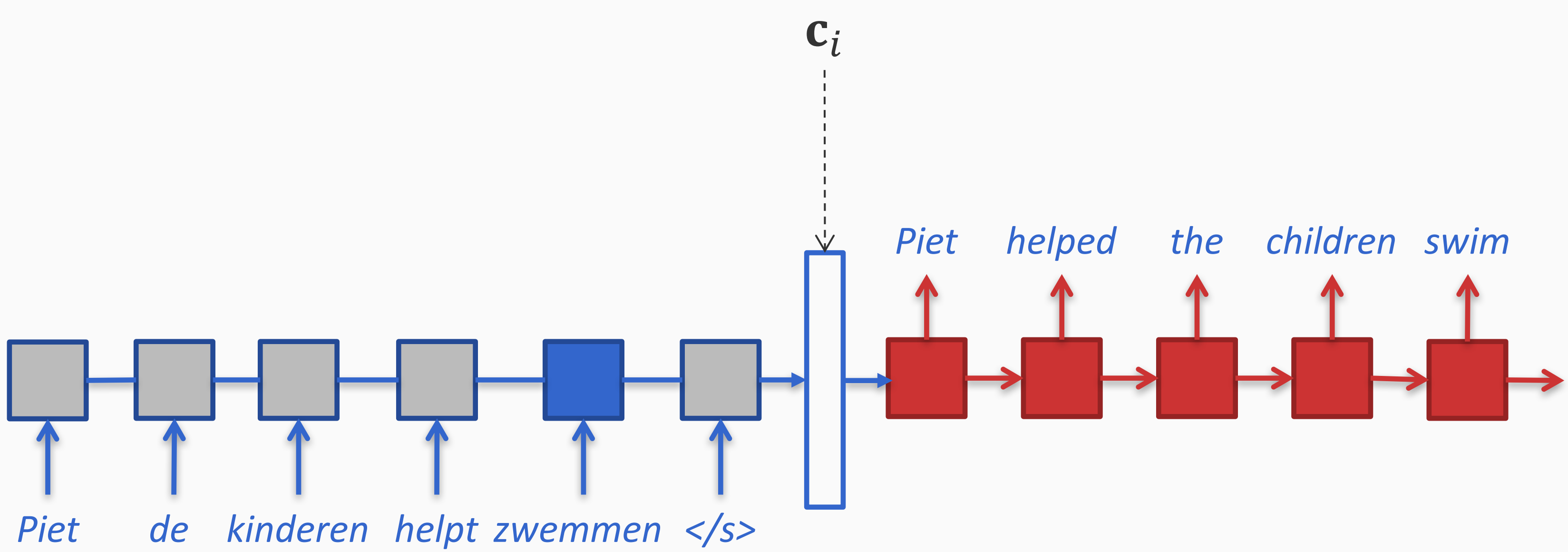

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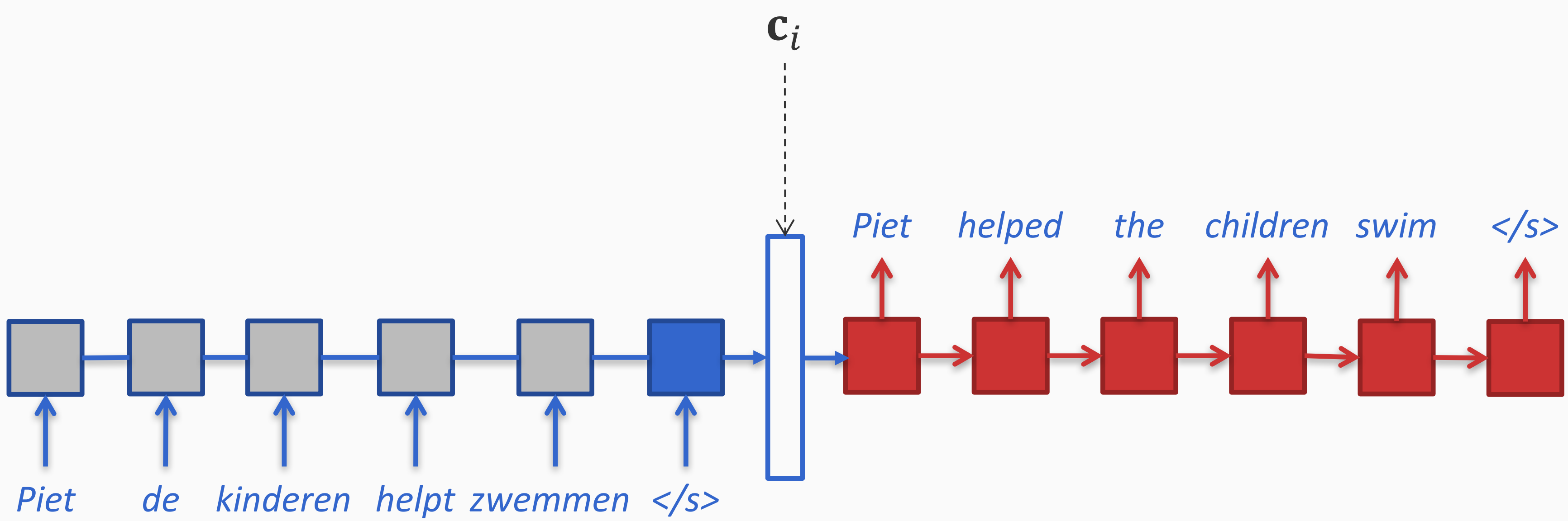

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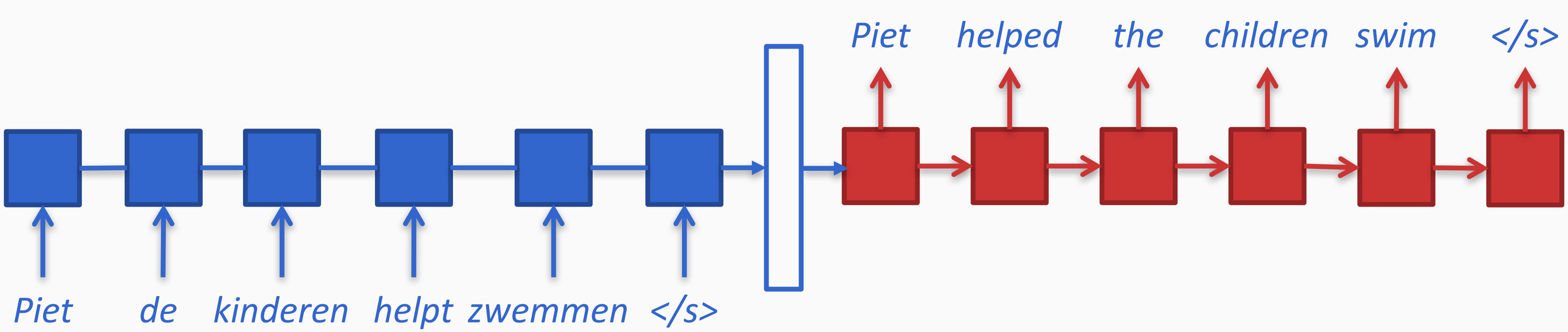
- At each step, this can be seen as a decision: *Which word is currently relevant?*



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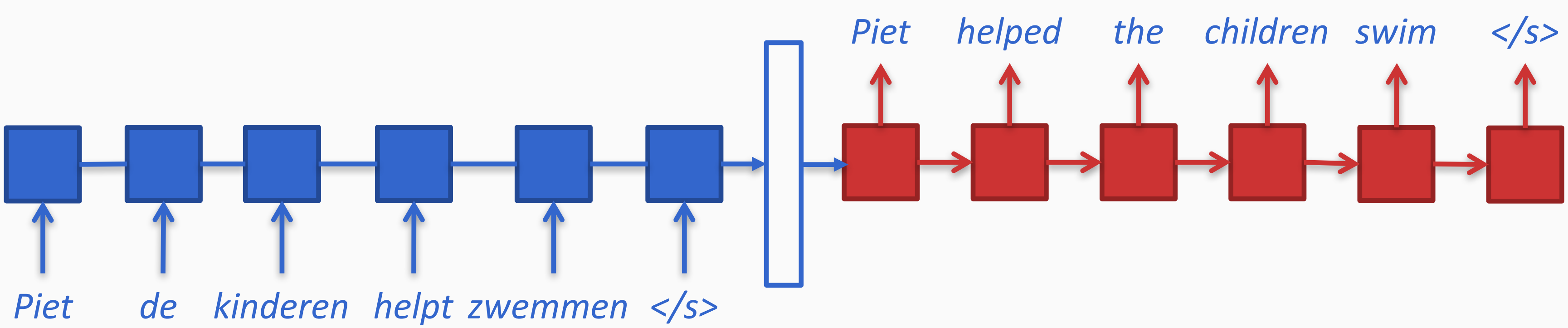
Instead of a hard decision, we can ask for a soft decision: a probability



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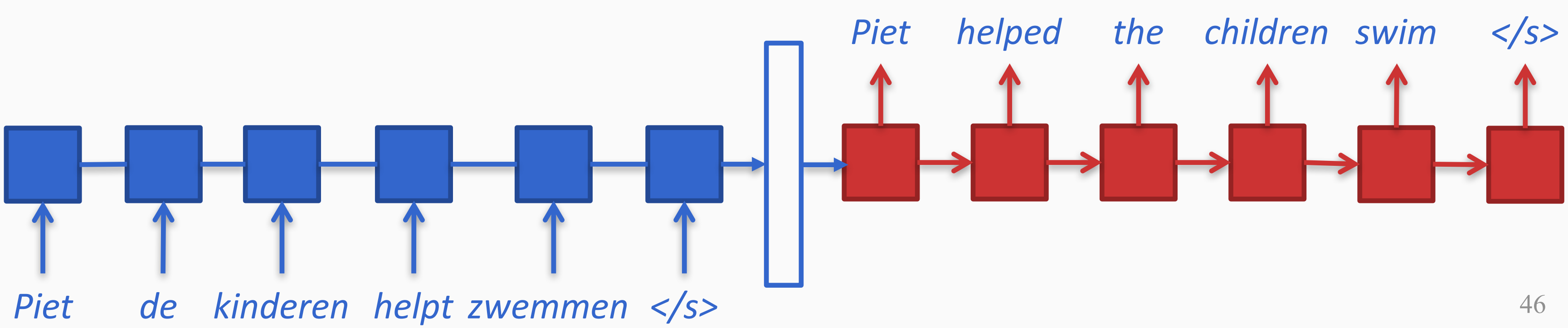
Let's see how we can construct the encoding using such a mechanism



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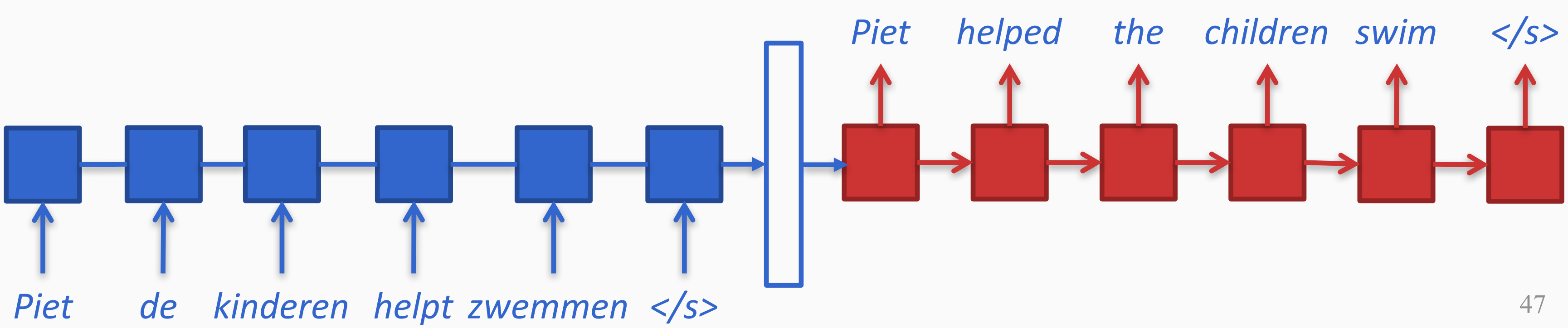

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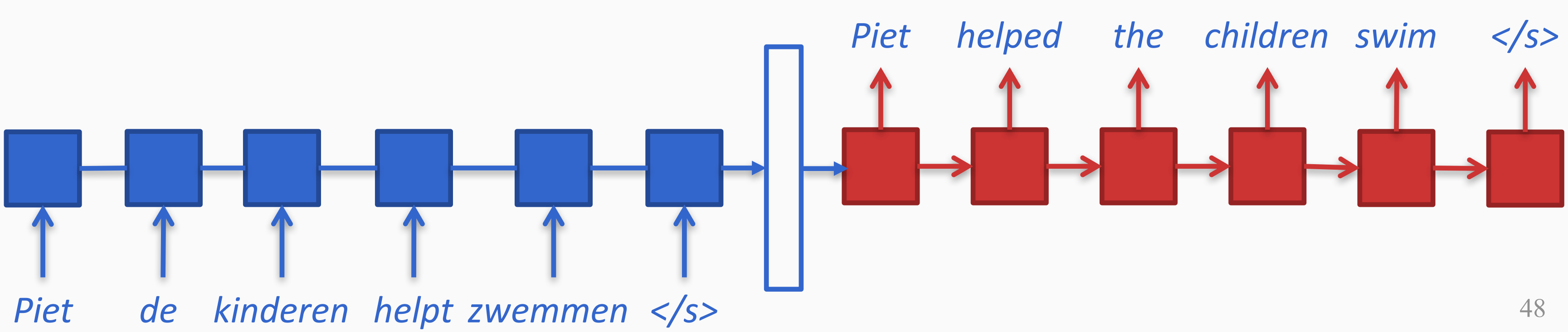

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A score that depends on the current state of the decoder and the word encodings

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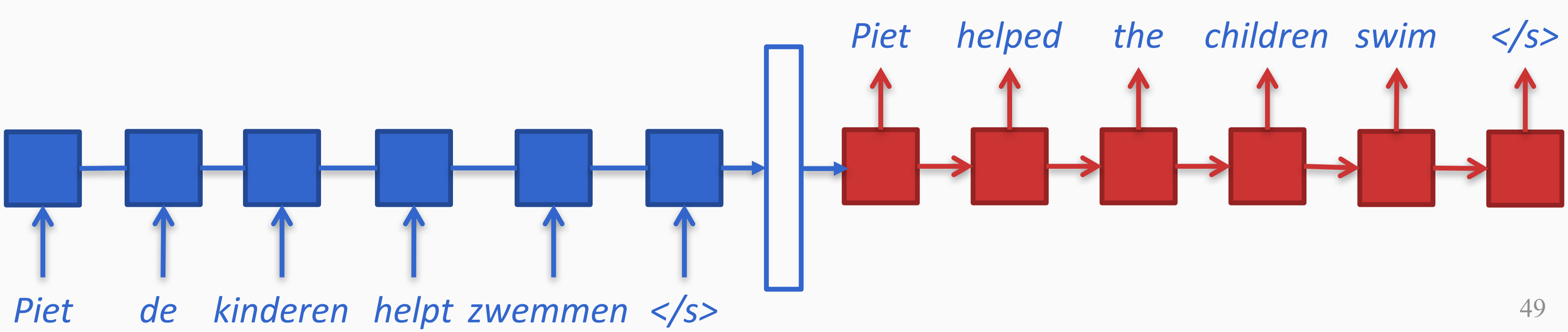
Characterizes how important the $j^{th}$ input word is at this point



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$$a(s_{i-1}, h_j) = W_a s_{i-1} + W_I h_j + b$$

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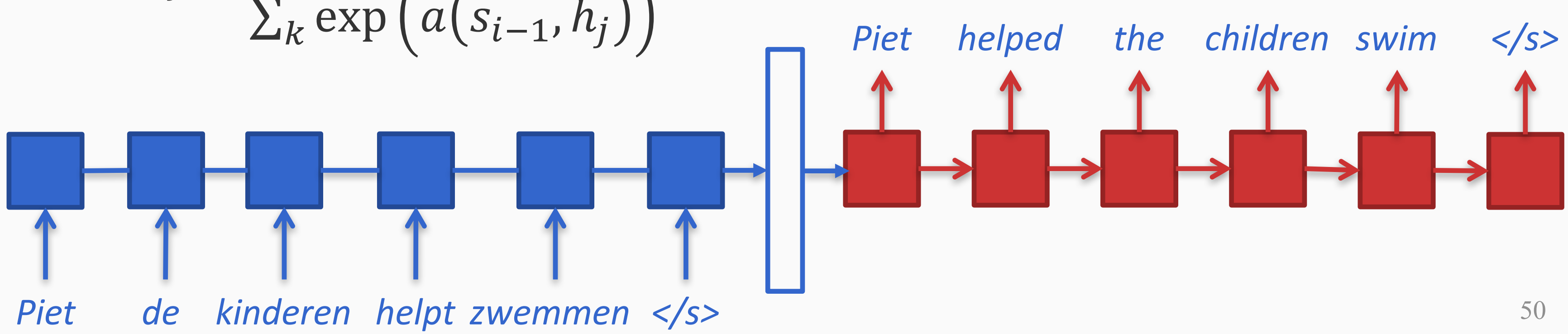

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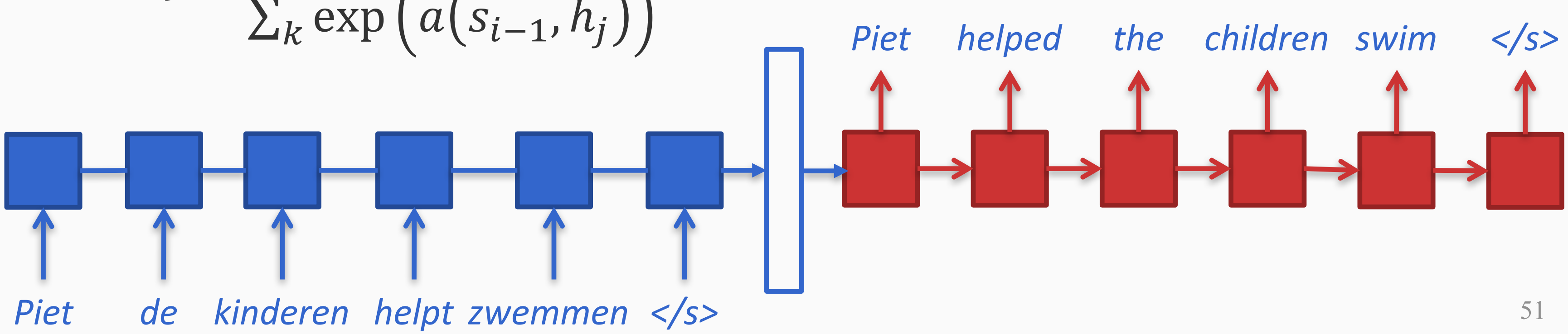
Convert this into a probability by taking softmax over the inputs

**What we have**: A distribution over inputs at each step of the decoder



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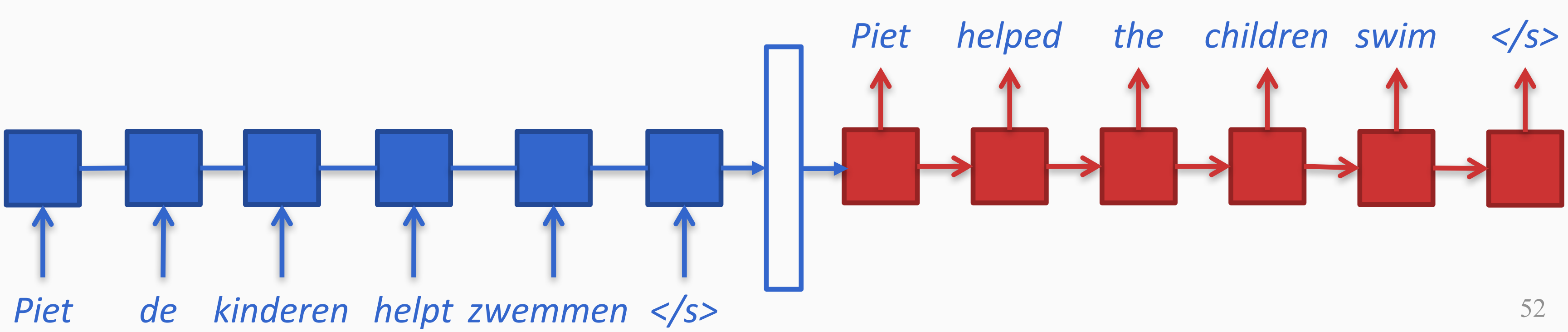

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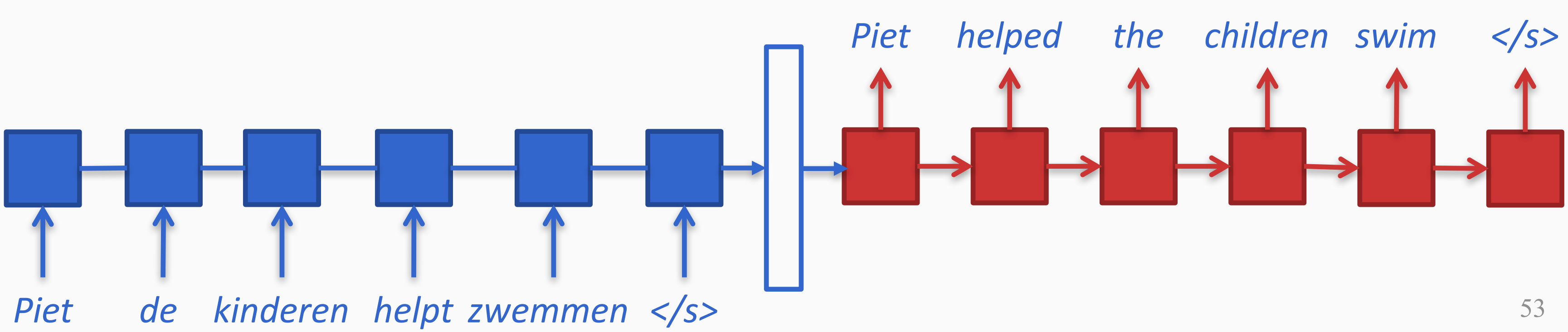
A weighted average of the word encodings



# Overview

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- Attention in encoder-decoder networks
- Various kinds of attention

# General idea of attention

- Given a prediction problem whose inputs consist of many sub-components
  - The sub-components may be encoded (e.g. with word embeddings, hidden states of RNNs)
  - Or they may be the intermediate nodes in a larger network
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- **The goal:** Find a distribution of the $\mathbf{h}_1, \mathbf{h}_2, \cdots$ that captures how relevant each of them are in the current state
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Sometimes this is called the ***source*** sequence

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# What we saw so far: Additive attention

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$$a(\mathbf{s}, \mathbf{h}_j) = \mathrm{W}_a \mathbf{s} + W_I \mathbf{h}_j + b$$

2. Normalize with softmax to get attention

$$\text{Attention } a_j = \frac{\exp\left(a(\mathbf{s}, \mathbf{h}_j)\right)}{\sum_k \exp\left(a(\mathbf{s}, \mathbf{h}_k)\right)}$$

# What we saw so far: Additive attention

1. Compute a score for each sub-component of the input

$$a(\mathbf{s}, \mathbf{h}_j) = \mathrm{W}_a\mathbf{s} + W_I\mathbf{h}_j + b$$

2. Normalize with softmax to get attention

$$\text{Attention } a_j = \frac{\exp\left(a(\mathbf{s}, \mathbf{h}_j)\right)}{\sum_k \exp(a(\mathbf{s}, \mathbf{h}_k))}$$

Why should the score be additive?
Maybe other functions are possible

# Different scoring functions for attention

| Name | Scoring function $a(\mathbf{s}, \mathbf{h}_j)$ | Reference |
|---|---|---|
| Additive attention | $W_{\mathbf{a}}\mathbf{s} + W_I\mathbf{h}_j + b$ | Bahdanau et al 2015 |

We have already seen this

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We will see this in more detail when we visit Transformers

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In all cases, after the scoring function is applied, we have a softmax to produce the attention probability

# Hard vs soft attention

- Attention is a probability over the input sub-components
  - How relevant is each component in the context of a state **s**?
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# Hard vs soft attention

- Attention is a probability over the input sub-components
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  - Also called soft attention
- What if there are *many* sub-components?
  - *Needs an expensive softmax*
  - Can we avoid this?
- Hard attention: Select one of the components – the argmax
  - Less computation
  - But not differentiable. Involves reinforcement learning for training

# Self-attention Also called *intra-attention*

- So far: We have a sequence of inputs and a separate description of the current state
  - We want to compute attention over the inputs

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  - In our notation from before, $\mathbf{s}$ is one of the $\mathbf{h}_j$'s

# Self-attention Also called *intra-attention*

- So far: We have a sequence of inputs and a separate description of the current state
  - We want to compute attention over the inputs
- Suppose the “current” state is an element of the sequence
  - And we repeat this for each element
  - In our notation from before, $\mathbf{s}$ is one of the $\mathbf{h}_j$’s
- Intuition: Compute attention over a sentence with respect to each word in the sentence
  - Captures interactions between the words of a sentence

# Self-attention example

Cheng et al 2016

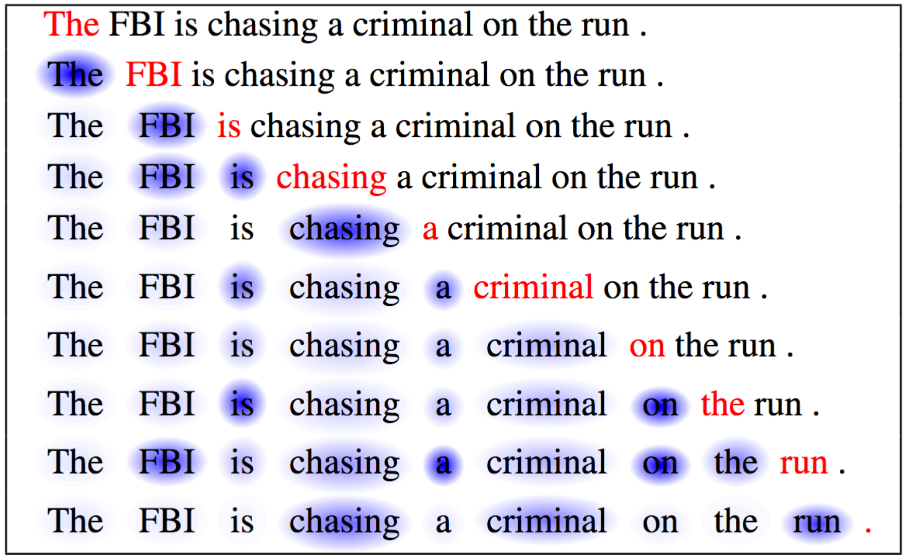


Figure 1: Illustration of our model while reading the sentence *The FBI is chasing a criminal on the run.* Color *red* represents the current word being fixated, *blue* represents memories. Shading indicates the degree of memory activation.

# Why is self-attention interesting?

- Allows for contextual encoding of words
  - Weighted average of the attended word encodings
- Unlike a recurrent neural network, there is no sequential dependencies
  - Better parallelism for contextual encodings
- Forms the basis of more sophisticated models such as the Transformer architecture