

Lecture 11: Seq2Seq + Attention

Alan Ritter

(many slides from Greg Durrett)

Recall: CNNs vs. LSTMs

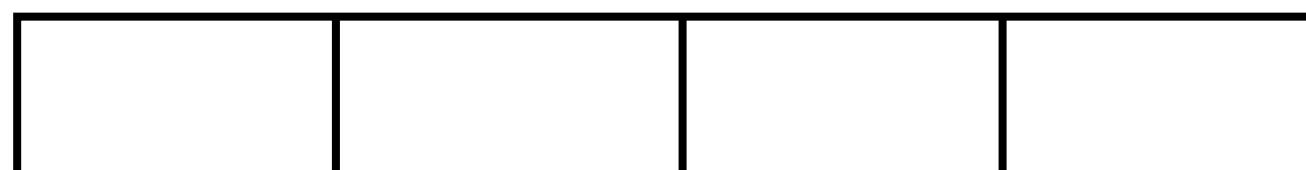


the movie was good

Recall: CNNs vs. LSTMs



c filters,
 $m \times k$ each



$n \times k$

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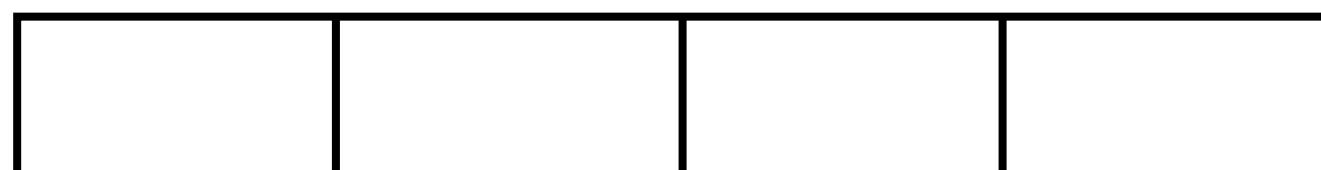
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$O(n) \times c$



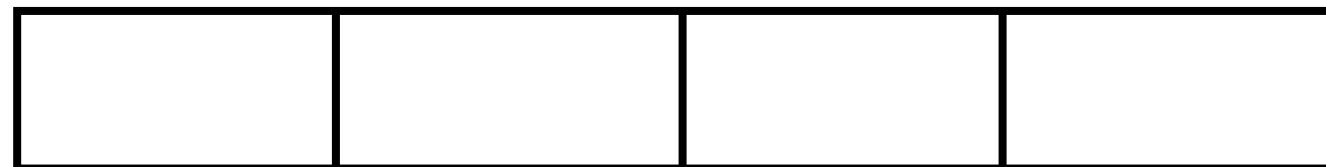
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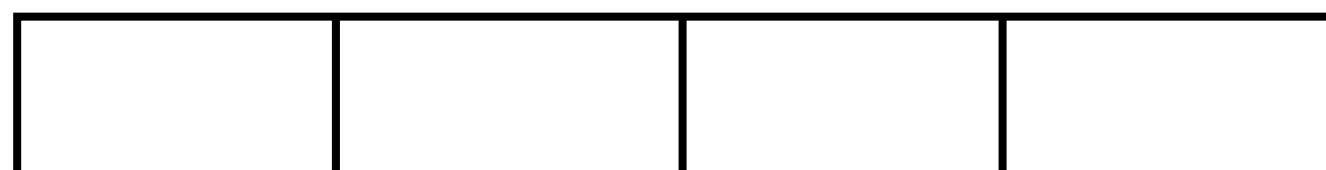
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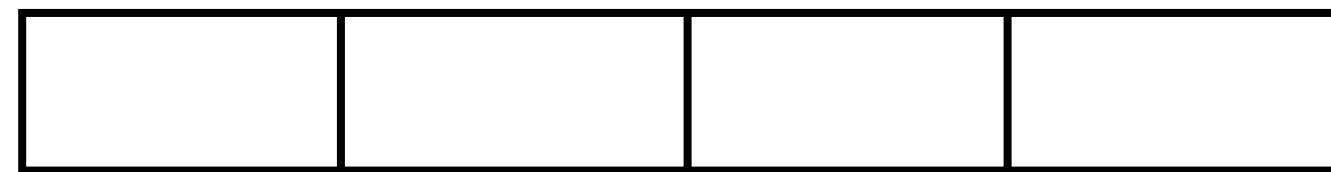


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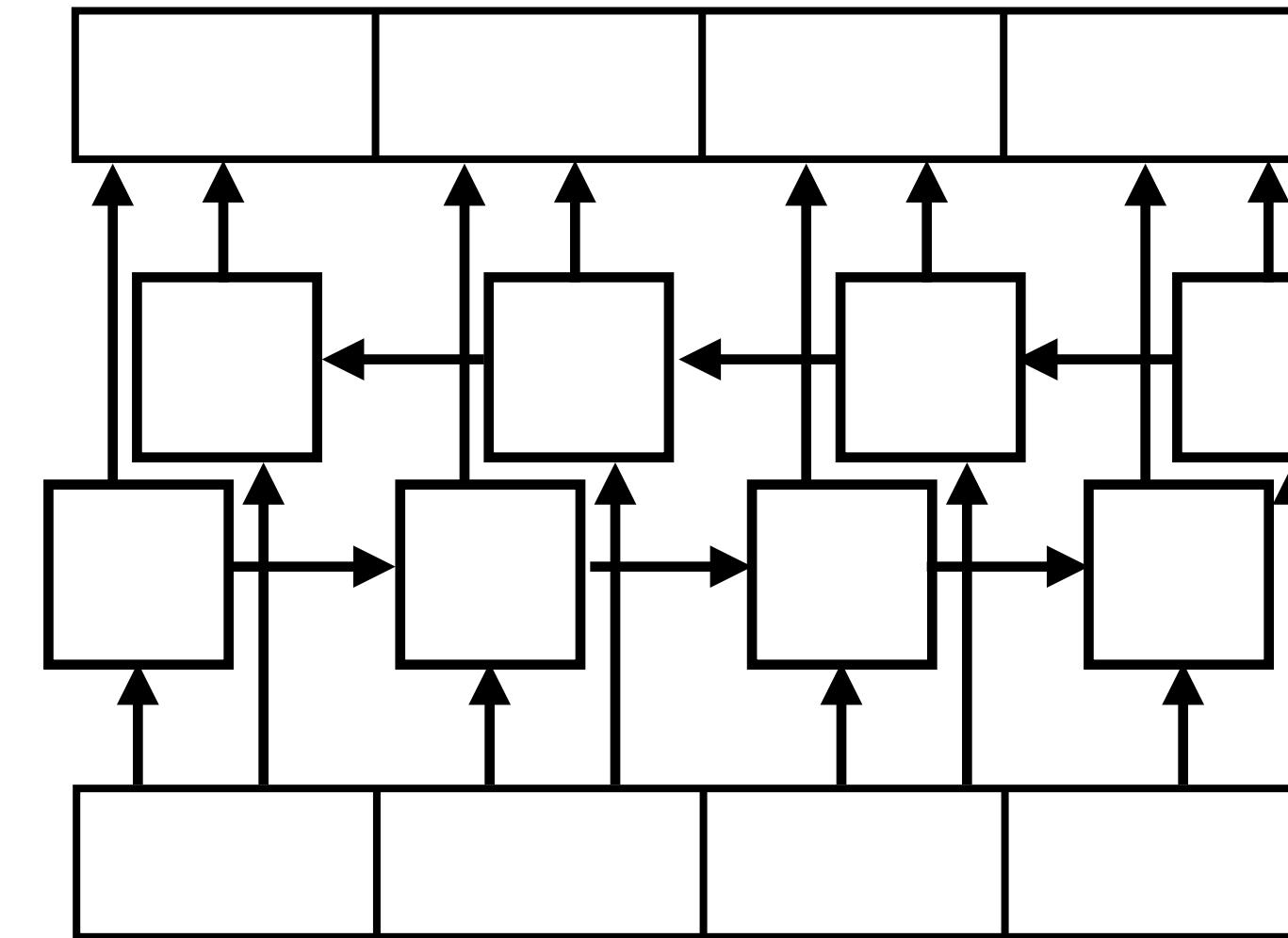


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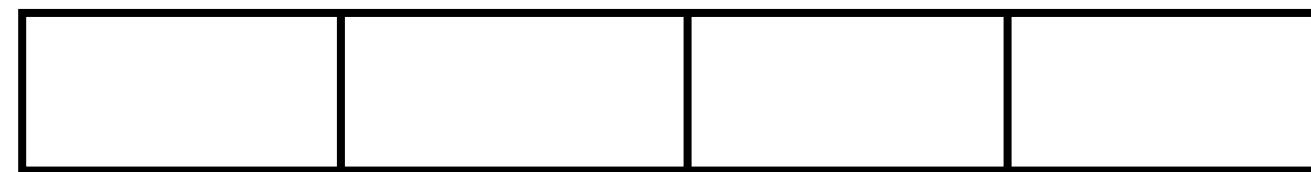
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BiLSTM with
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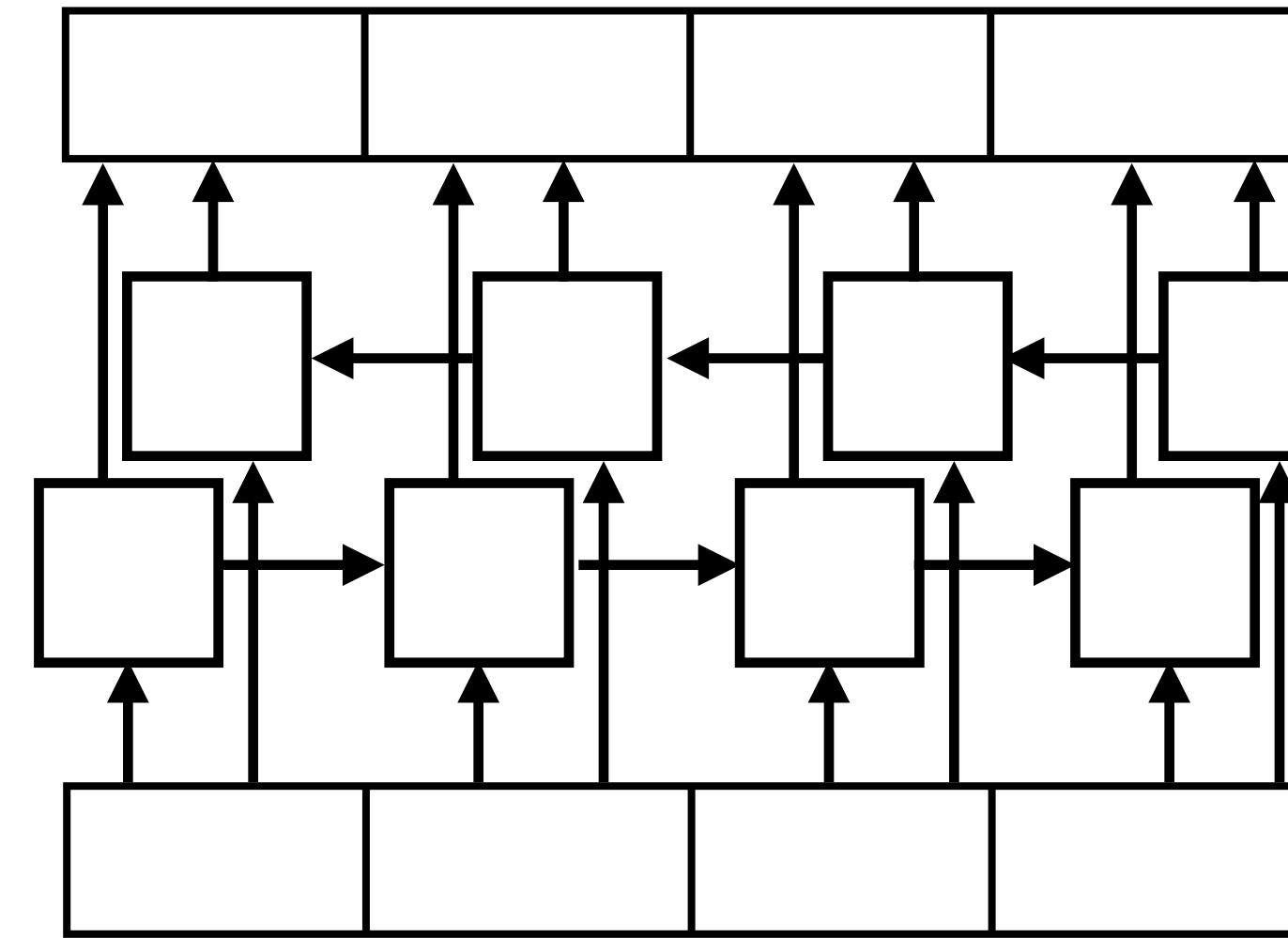


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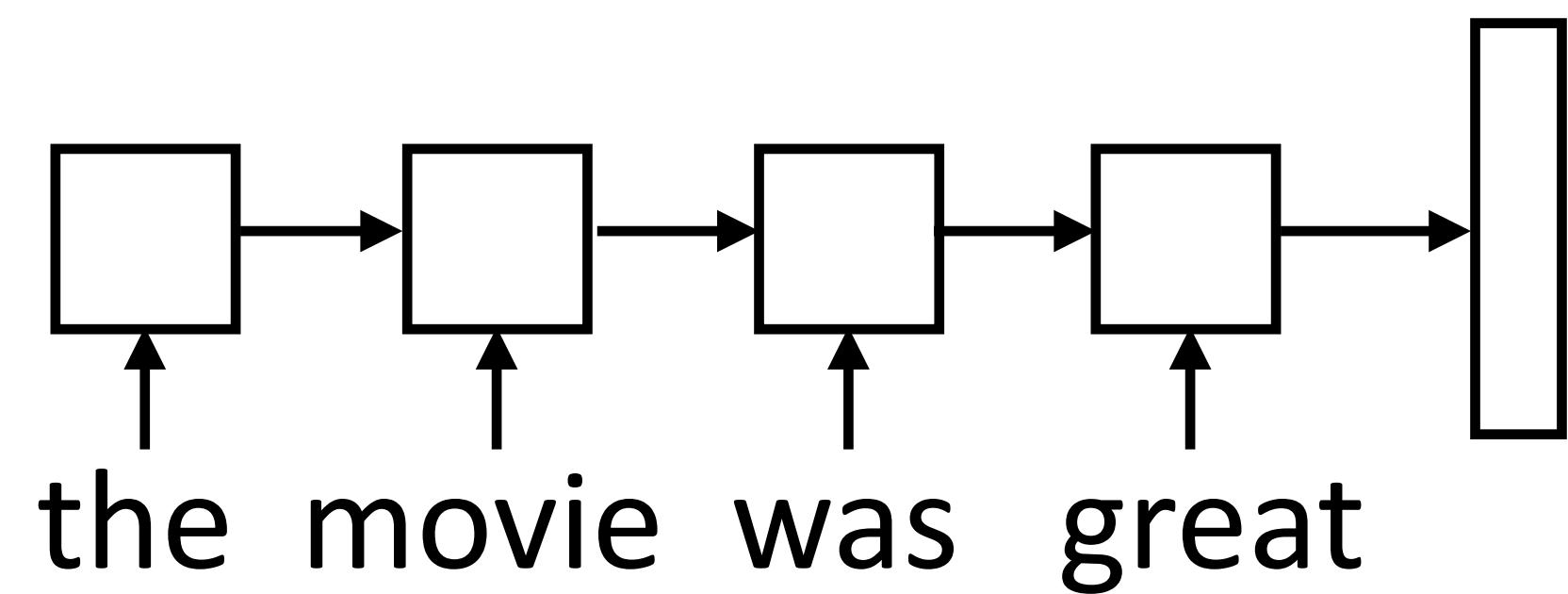
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the movie was good

- ▶ Both LSTMs and convolutional layers transform the input using context
- ▶ LSTM: “globally” looks at the entire sentence (but local for many problems)
- ▶ CNN: local depending on filter width + number of layers

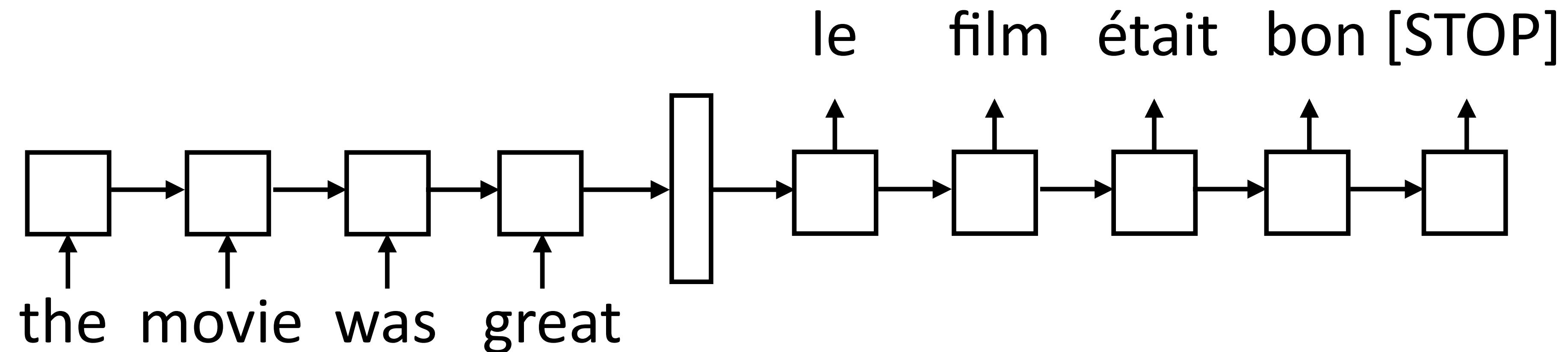
Encoder-Decoder

- ▶ Encode a sequence into a fixed-sized vector



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- ▶ Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Encoder-Decoder

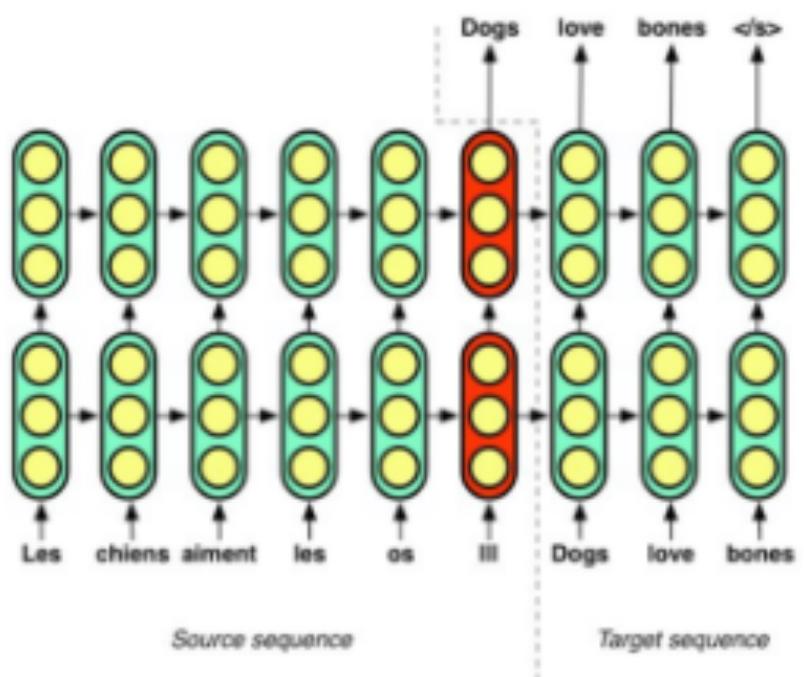


Edward Grefenstette
@egrefen

Follow

It's not an ACL tutorial on vector representations of meaning if there's at least one Ray Mooney quote.

A Transduction Bottleneck



Single vector representations cause problems.

- Training focusses on learning marginal language model of target language first.
- Longer input sequences cause compressive loss.
- Encoder gets significantly diminished gradient.

In the words of Ray Mooney...

"You can't cram the meaning of a whole %&!\$ing sentence into a single \$&!*ing vector!"

Yes, the censored-out swearing is copied verbatim.

► Is this true? Sort of...we'll come back to this later

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Xiaodan Zhu & Edward Grefenstette

DL for Composition

July 30th, 2017

35 / 109

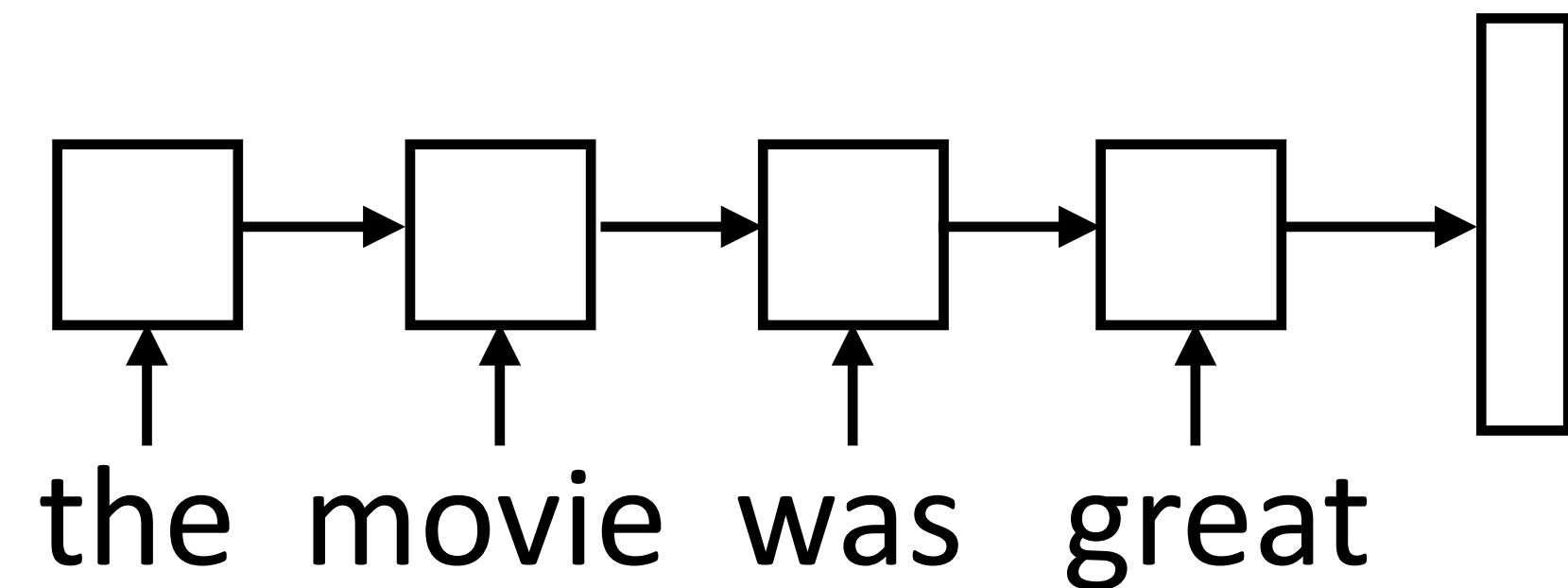
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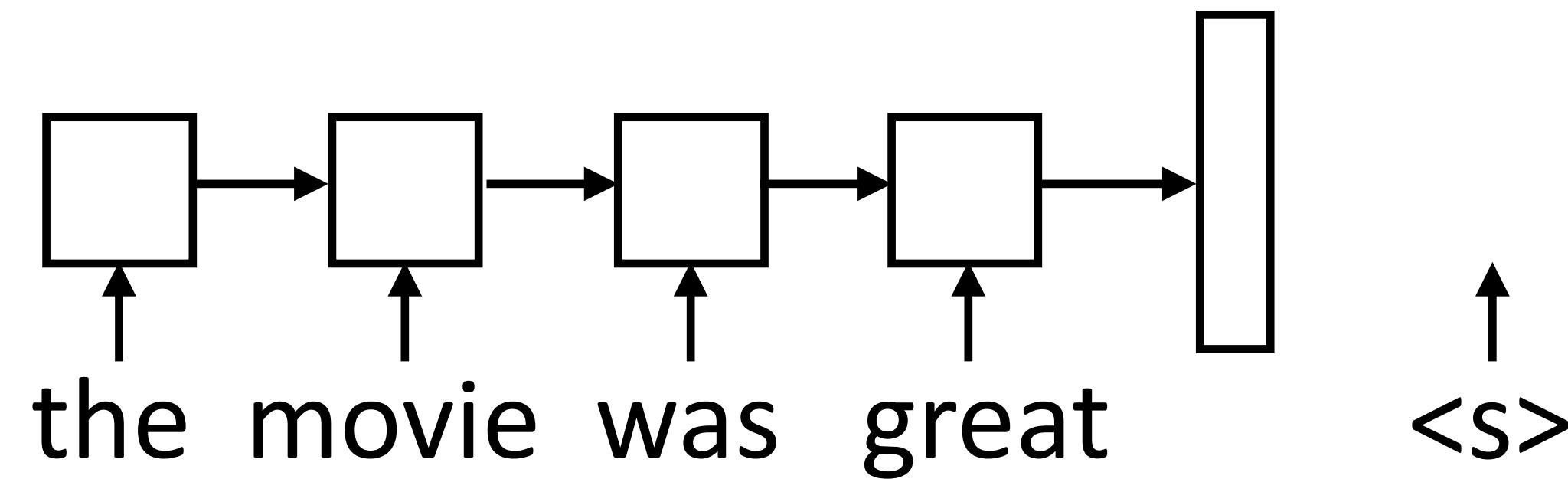
Model

- ▶ Generate next word conditioned on previous word as well as hidden state



Model

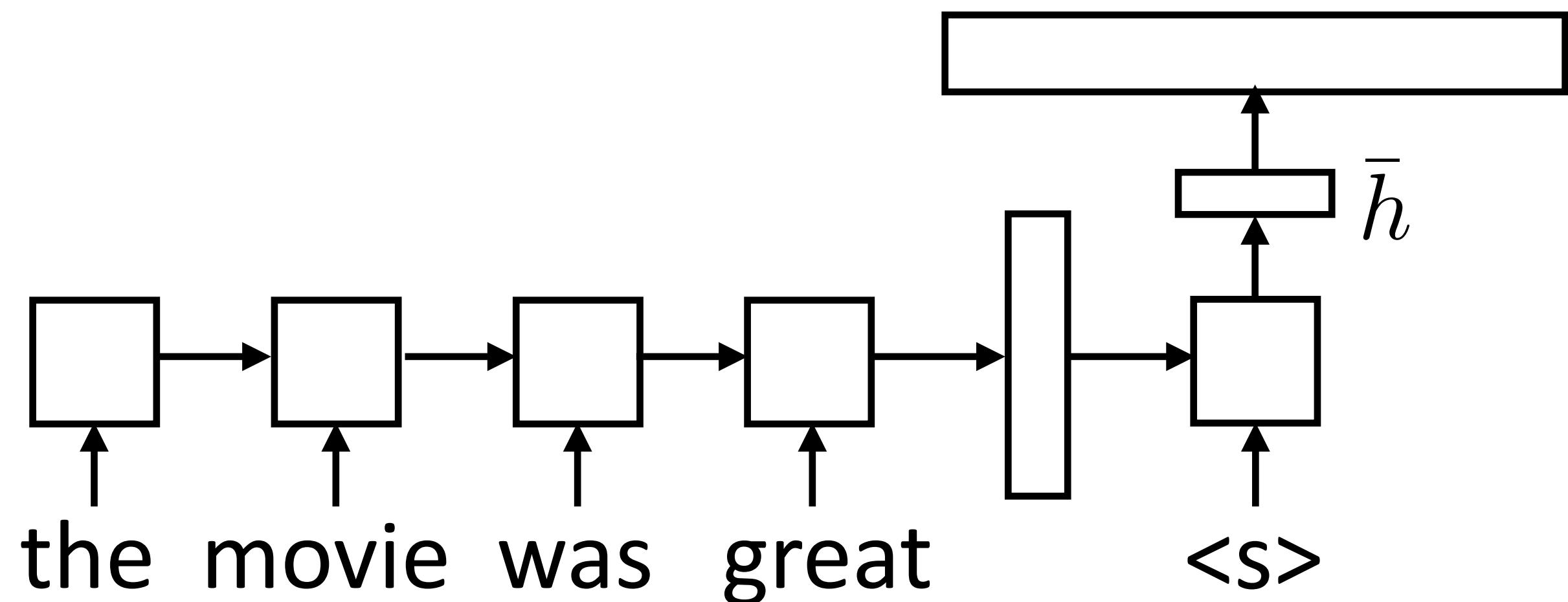
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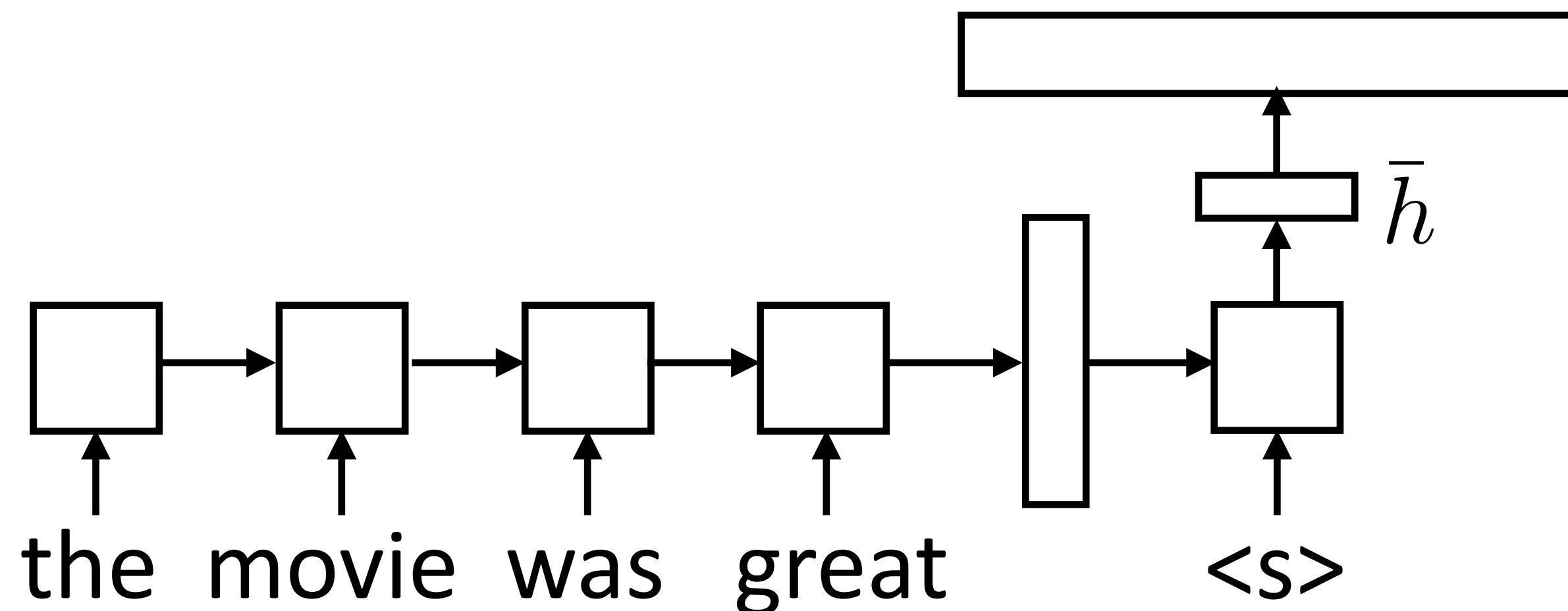
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- ▶ W size is $|\text{vocab}| \times |\text{hidden state}|$, softmax over entire vocabulary

$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W\bar{h})$$



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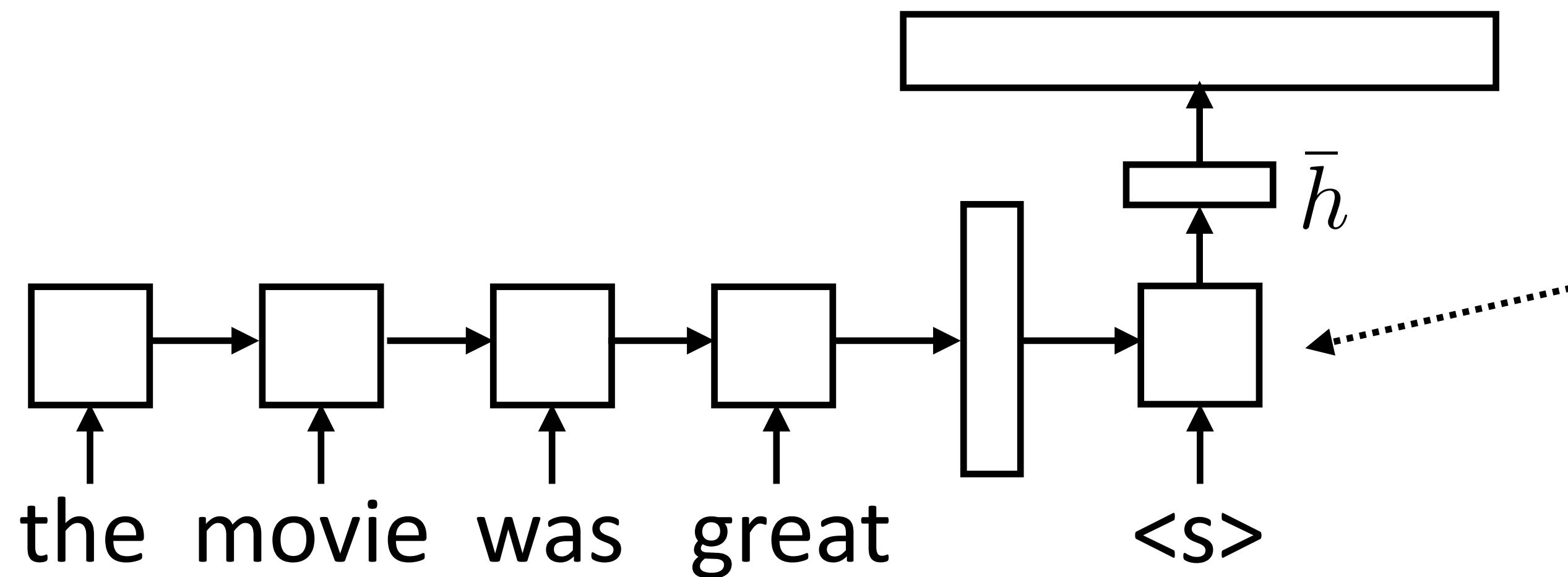


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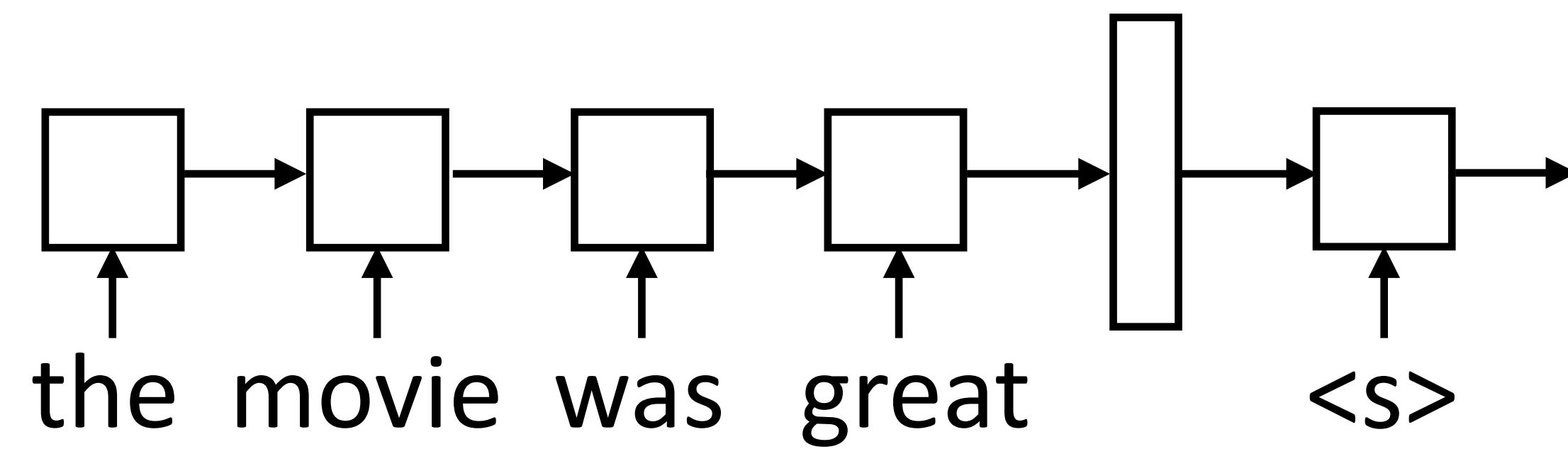
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Decoder has separate parameters from encoder, so this can learn to be a language model (produce a plausible next word given current one)

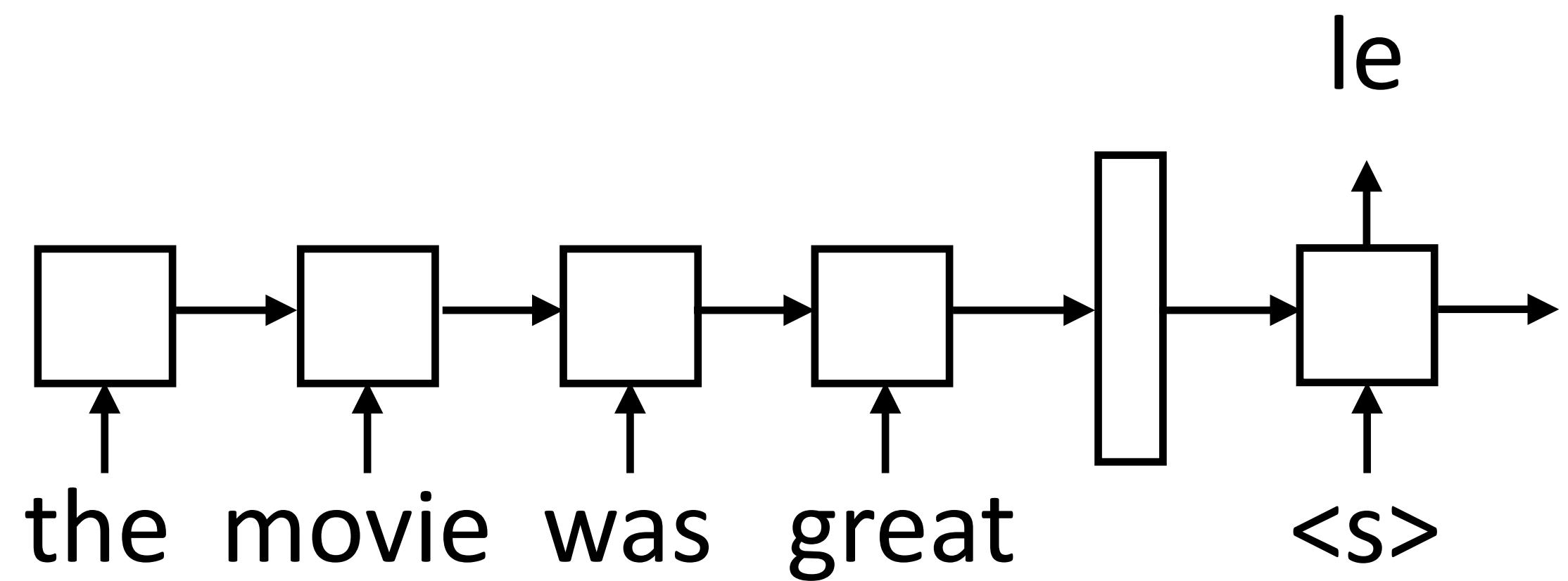
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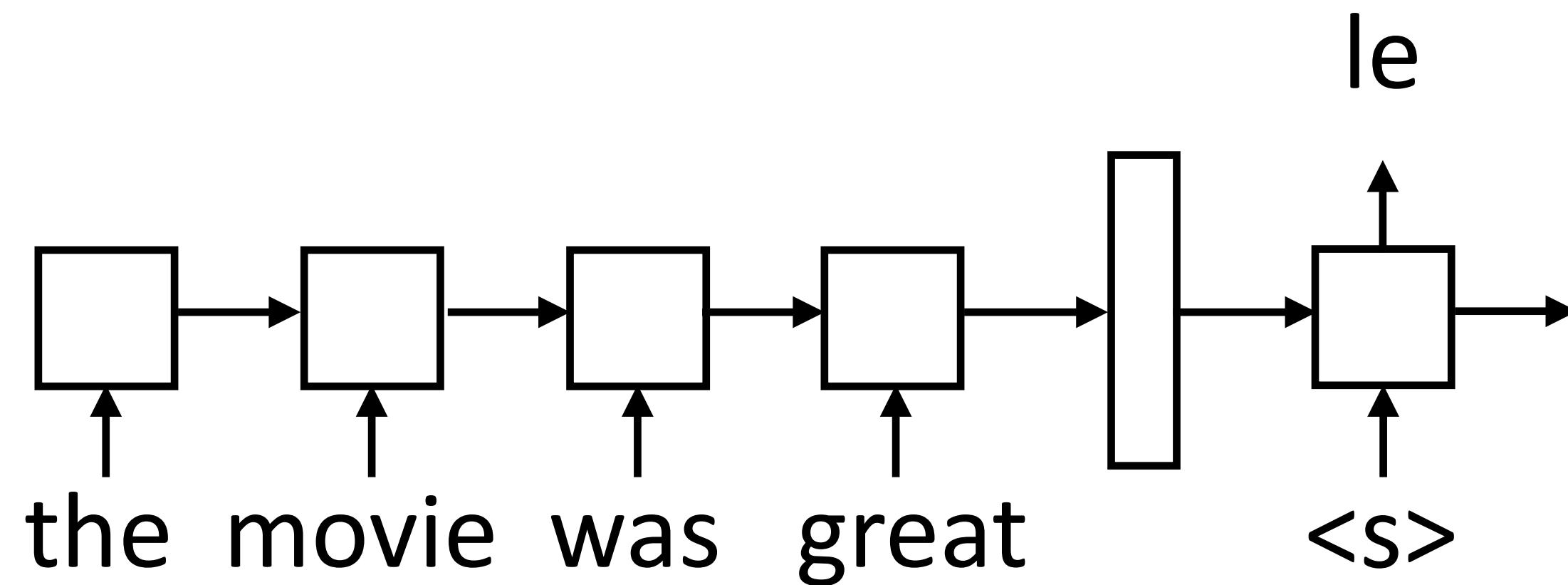
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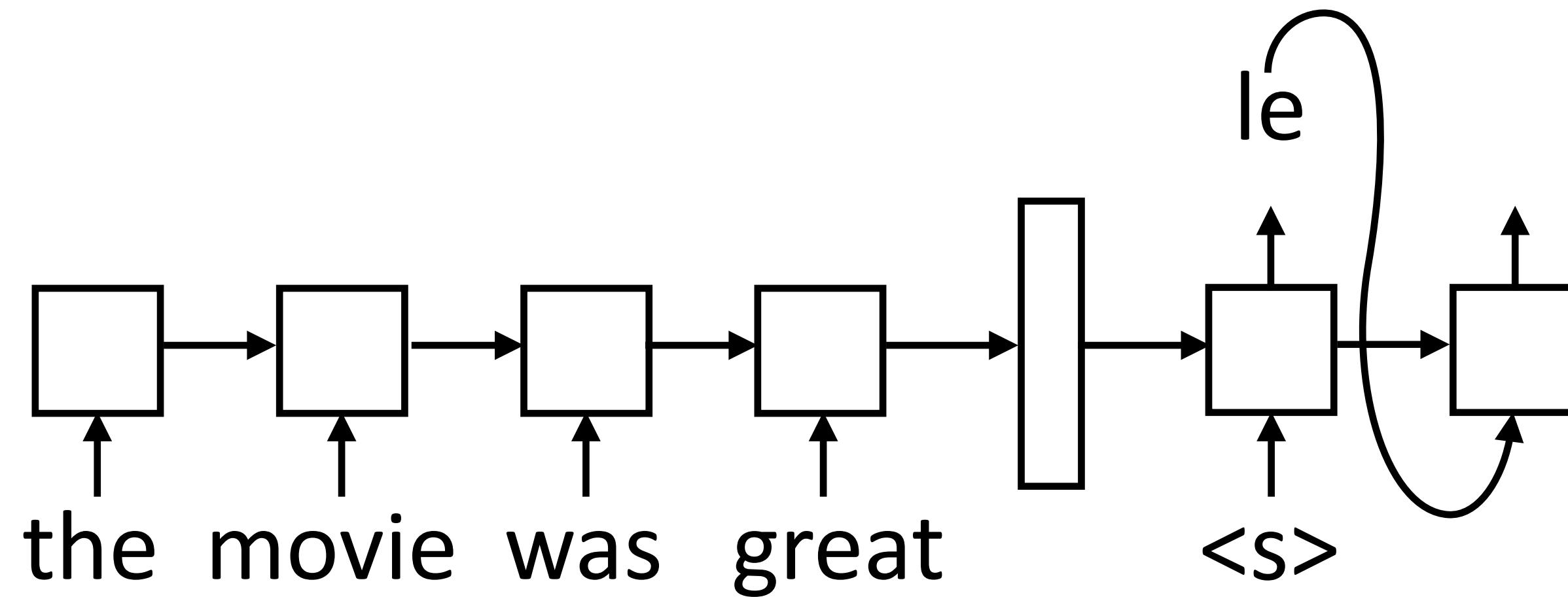
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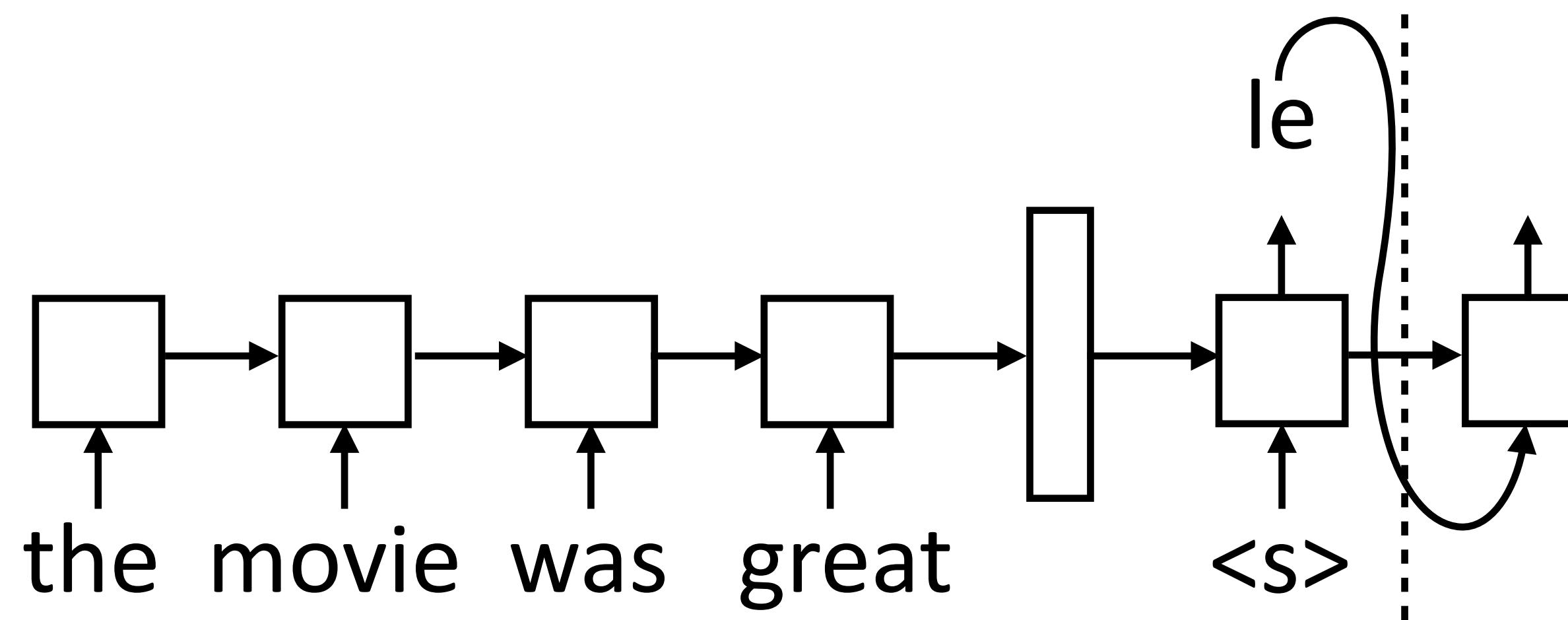
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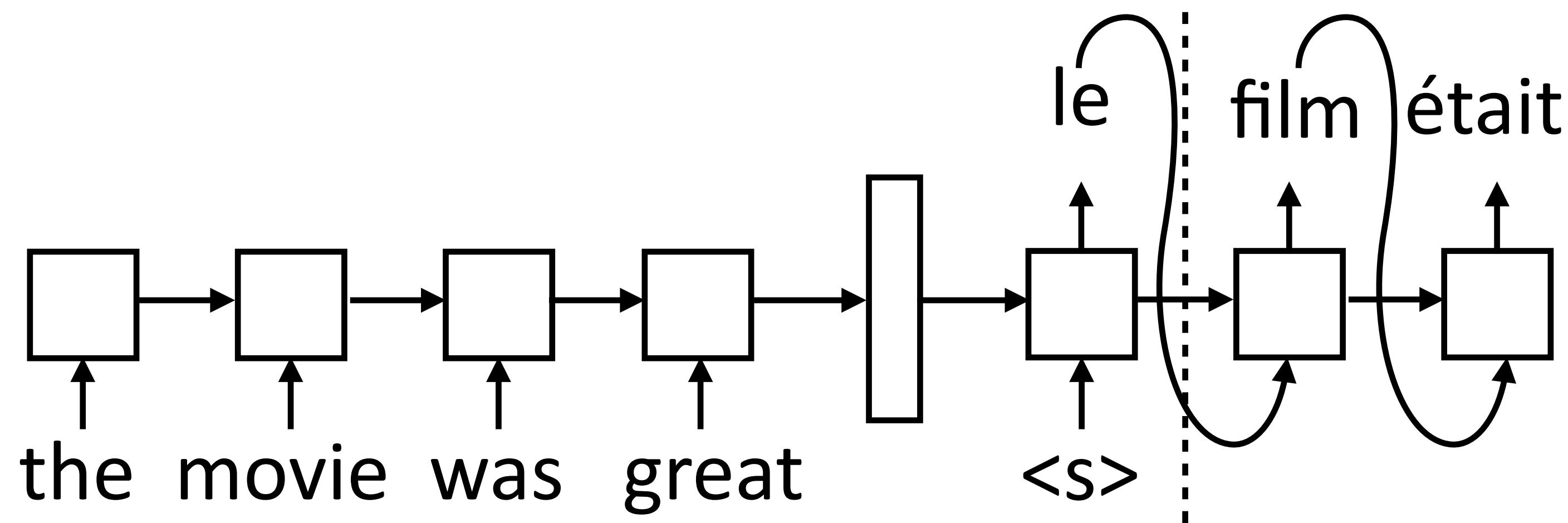
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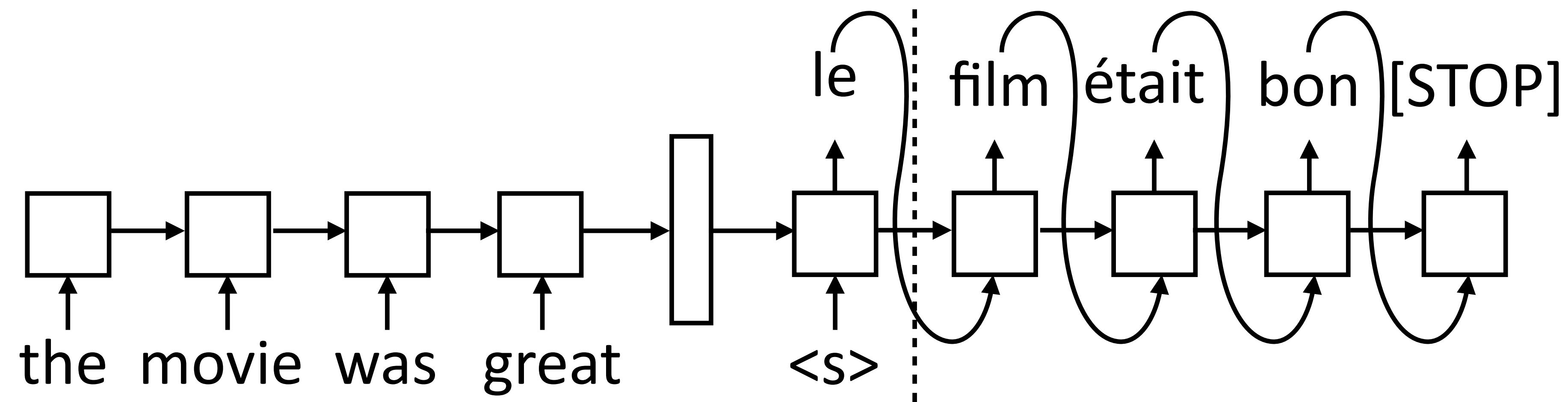
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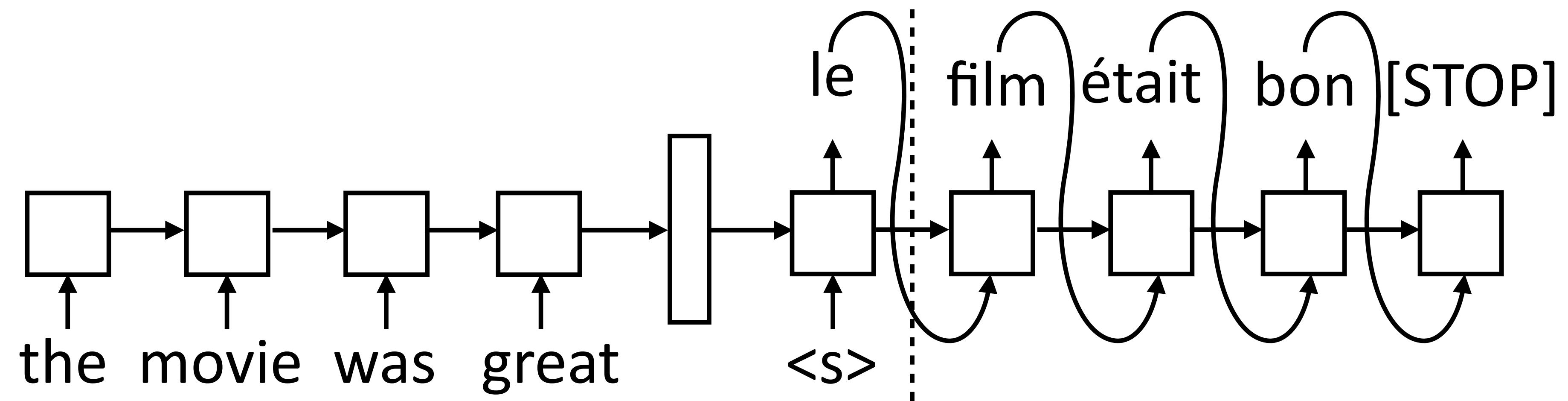
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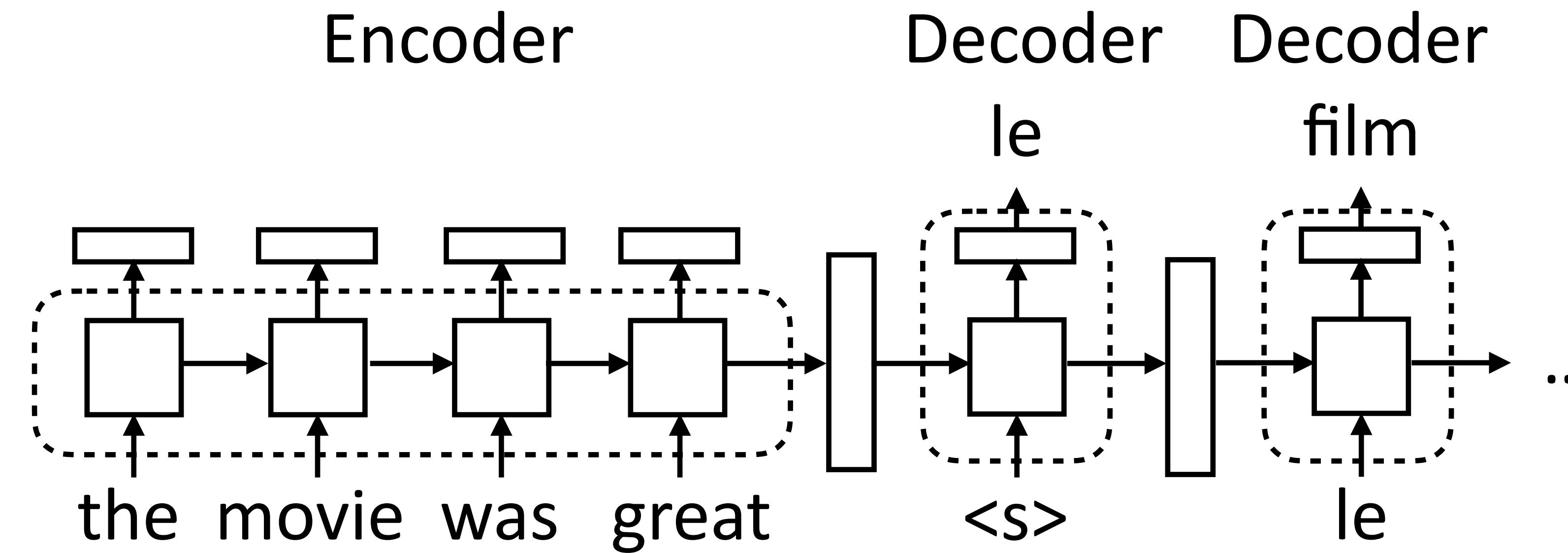
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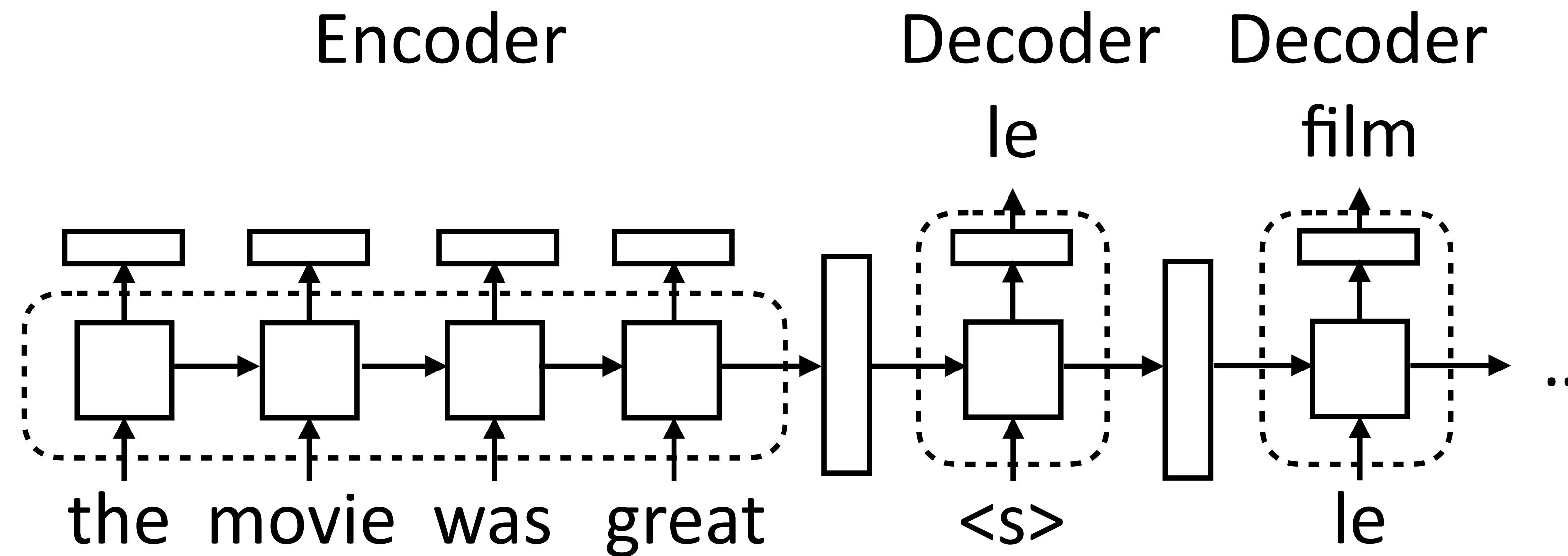


- ▶ During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- ▶ Need to actually evaluate computation graph up to this point to form input for the next state
- ▶ Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models

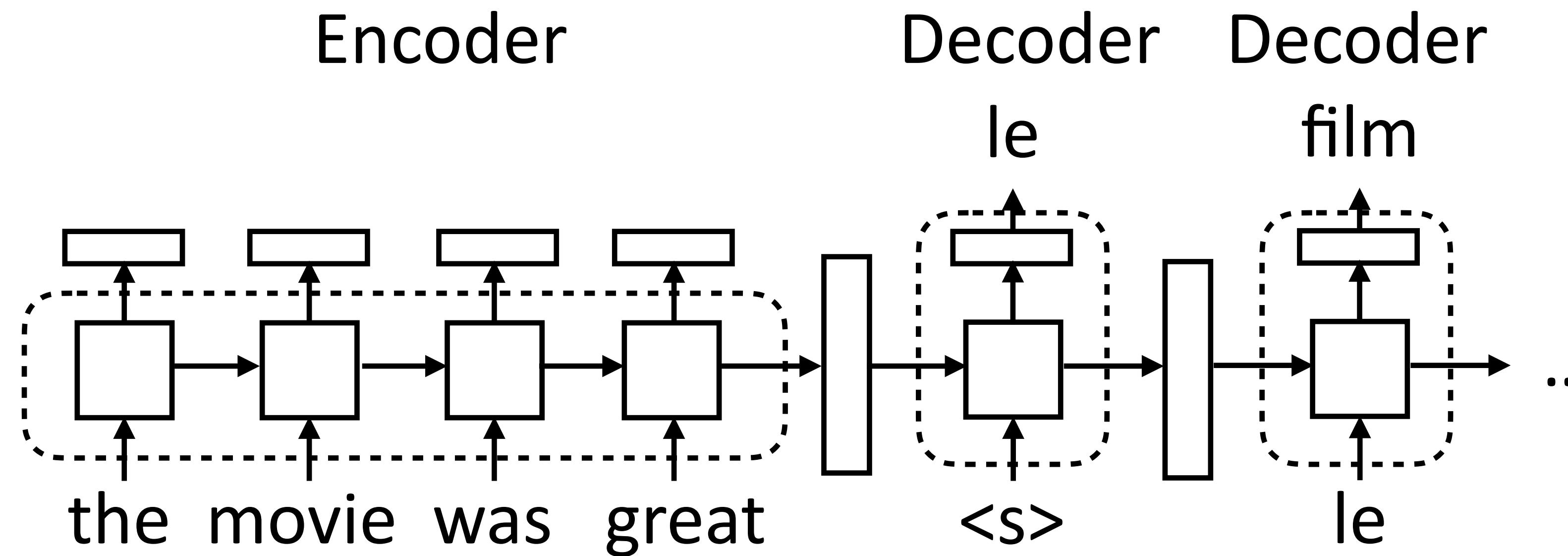


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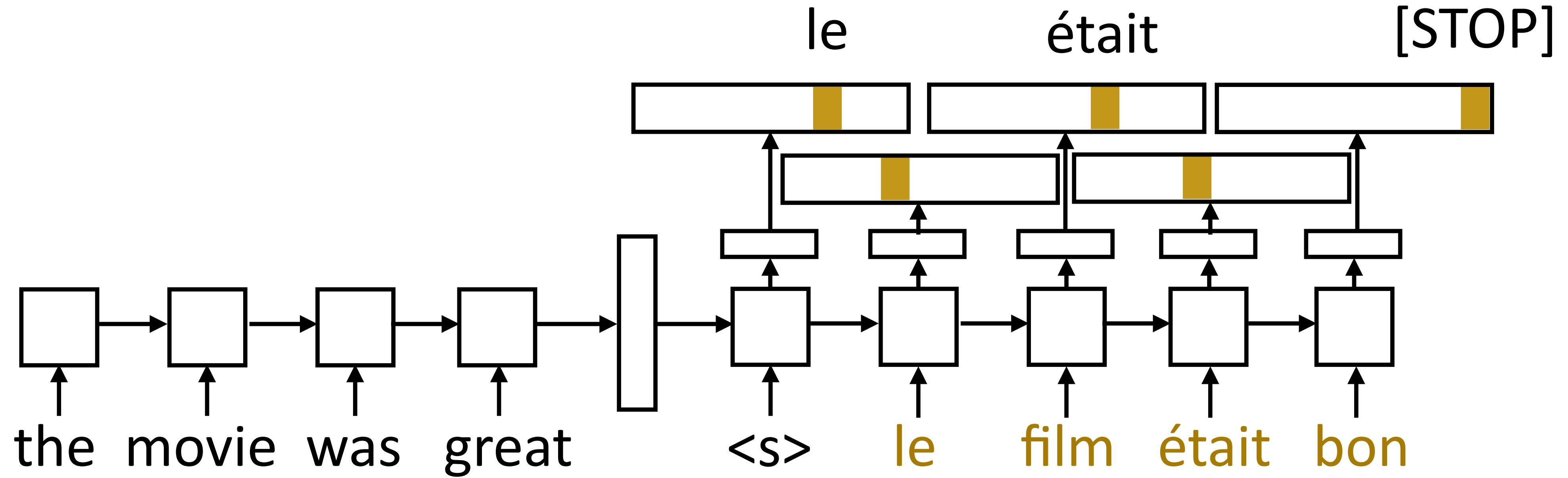
- ▶ Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks

Implementing seq2seq Models



- ▶ Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks
- ▶ Decoder: separate module, single cell. Takes two inputs: hidden state (vector h or tuple (h, c)) and previous token. Outputs token + new state

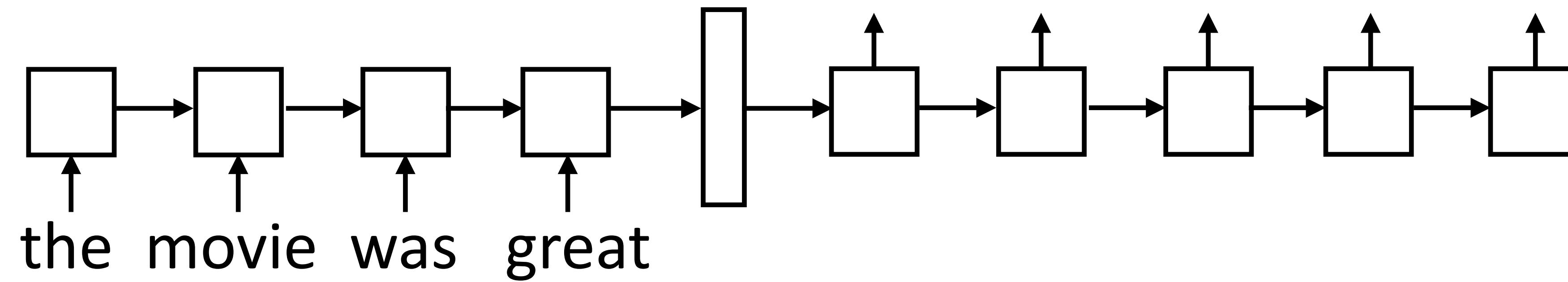
Training



- ▶ Objective: maximize $\sum_{(\mathbf{x}, \mathbf{y})} \sum_{i=1}^n \log P(y_i^* | \mathbf{x}, y_1^*, \dots, y_{i-1}^*)$
- ▶ One loss term for each target-sentence word, feed the correct word regardless of model's prediction

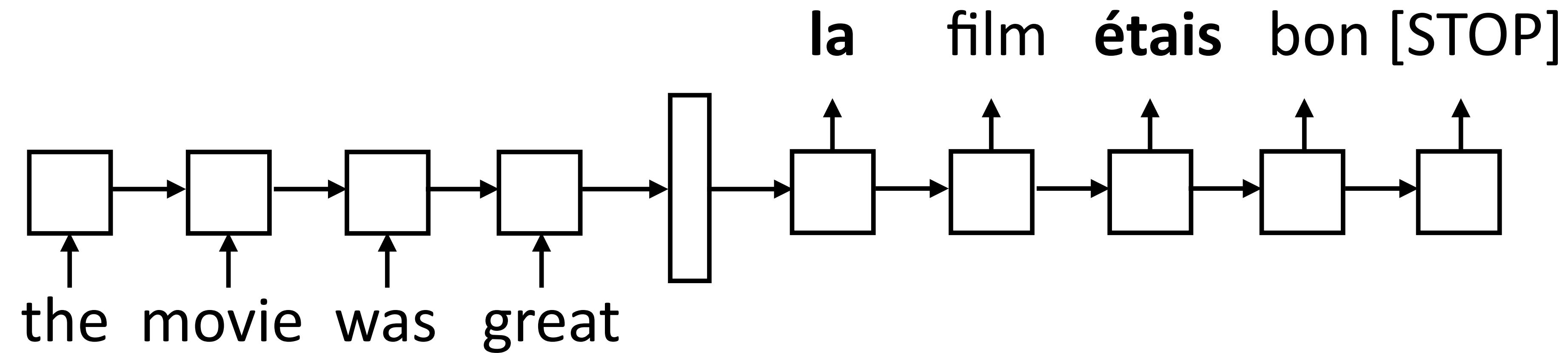
Training: Scheduled Sampling

- ▶ Model needs to do the right thing even with its own predictions



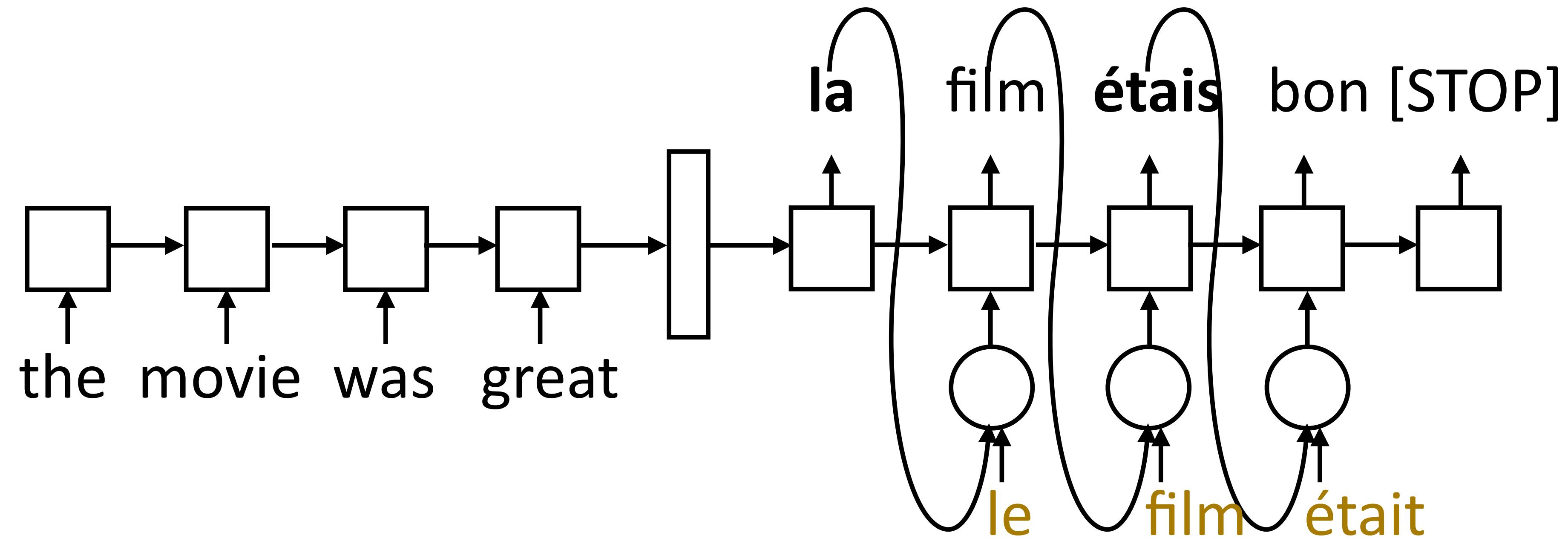
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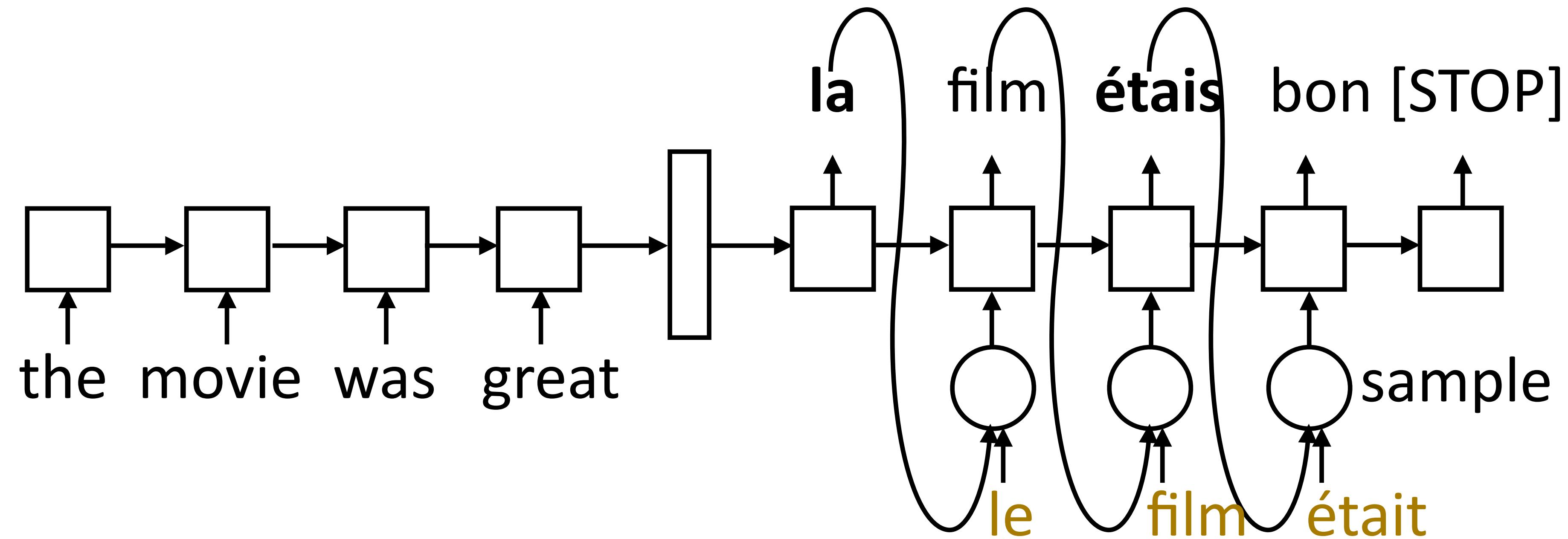
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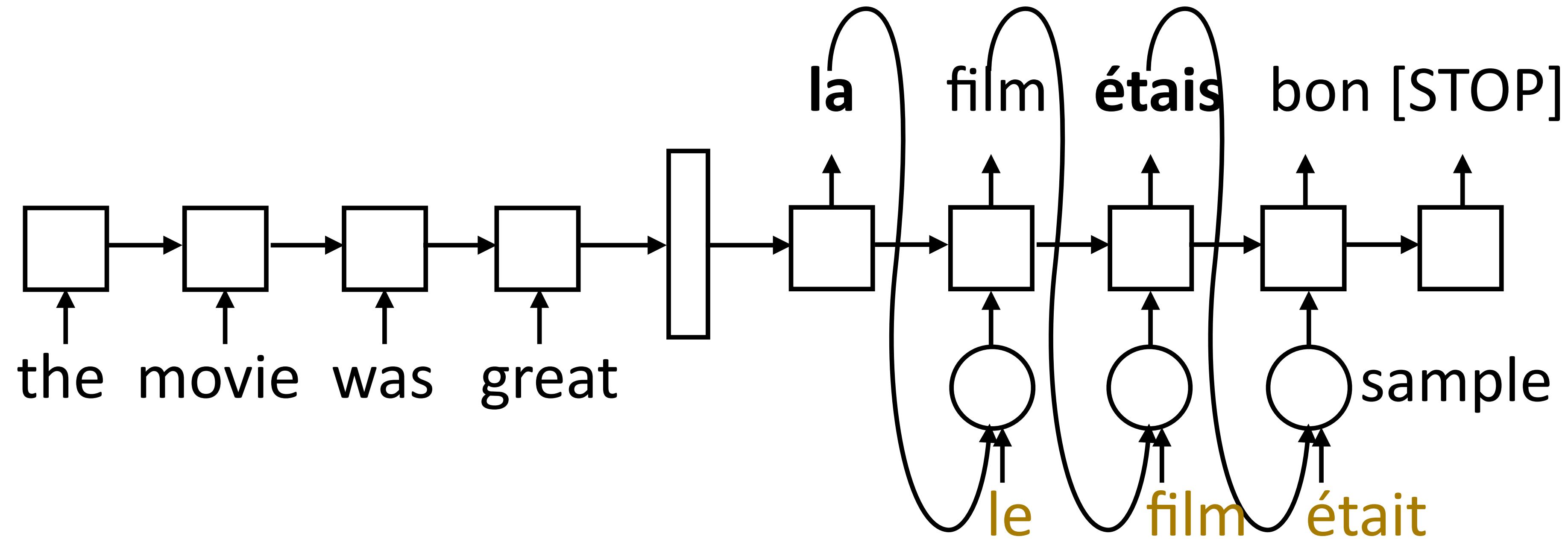
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- ▶ Scheduled sampling: with probability p , take the gold as input, else take the model's prediction
- ▶ Starting with $p = 1$ and decaying it works best
- ▶ Ideally (in theory), use RL for this...

Bengio et al. (2015)

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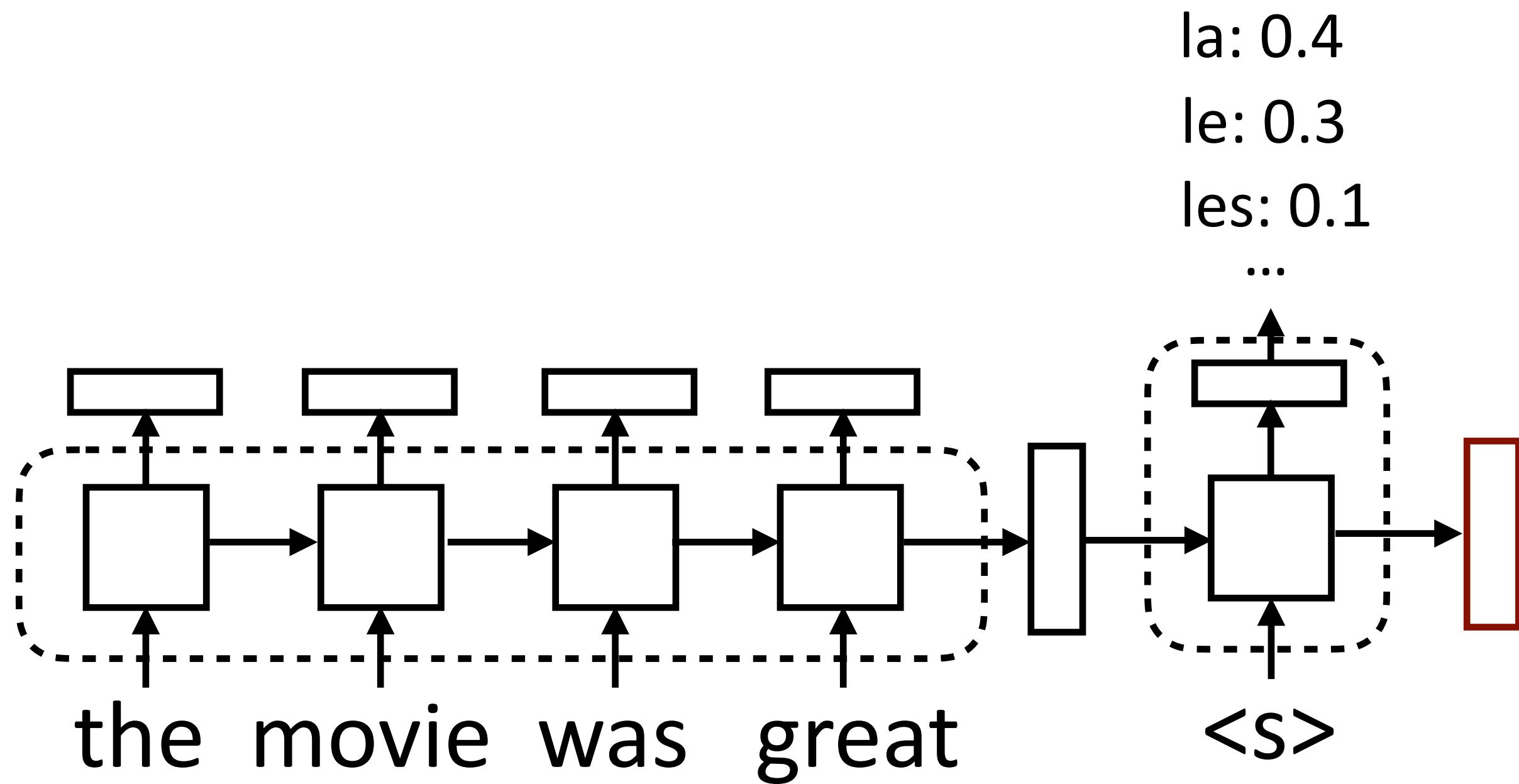
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- ▶ Decoder: also flexible in terms of architecture (more later). Execute one step of computation at a time, so computation graph is formulated as taking one input + hidden state
- ▶ Beam search: can help with lookahead. Finds the (approximate) highest scoring sequence:

$$\operatorname{argmax}_{\mathbf{y}} \prod_{i=1}^n P(y_i | \mathbf{x}, y_1, \dots, y_{i-1})$$

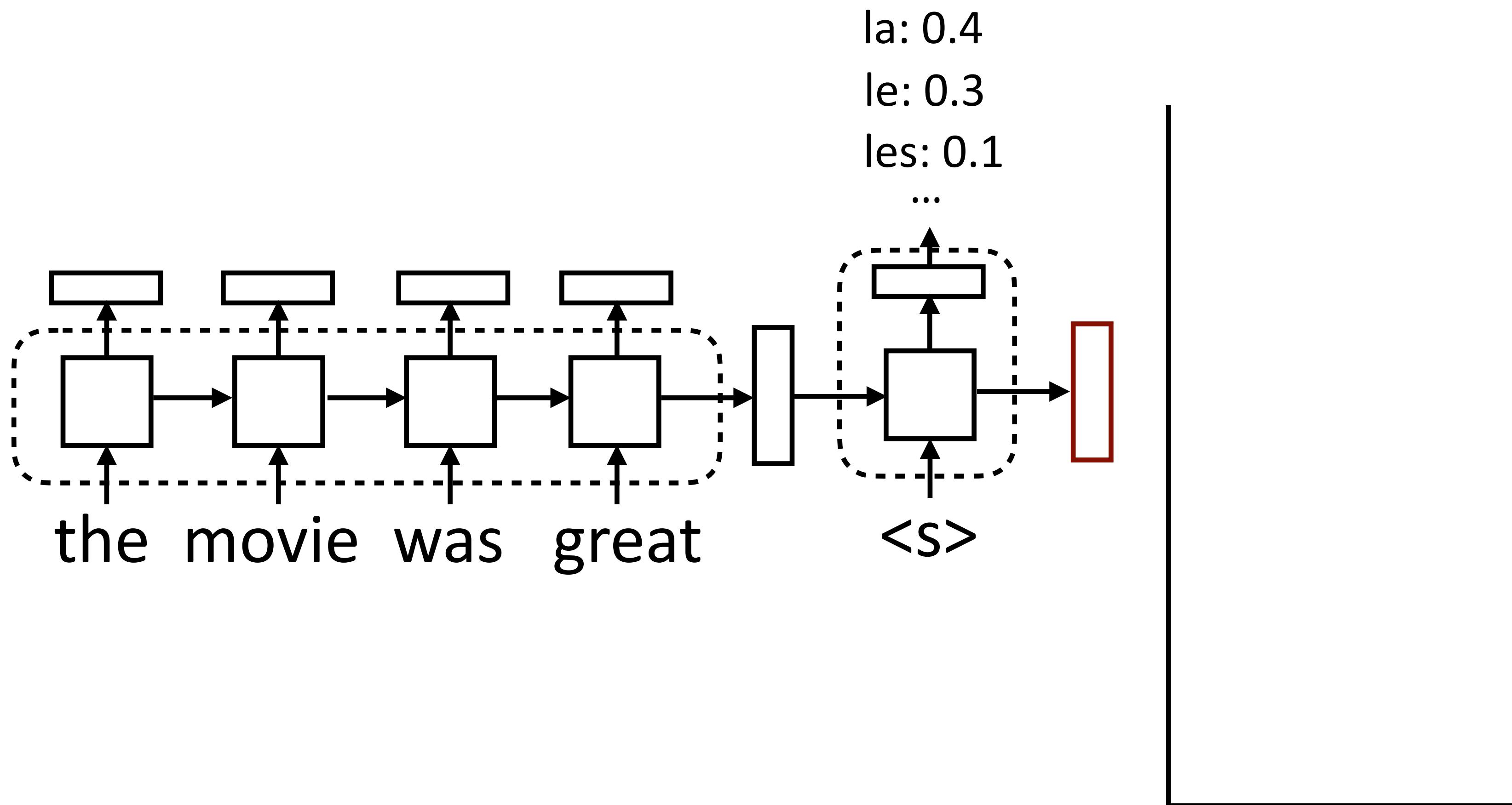
Beam Search

- Maintain decoder state, token history in beam



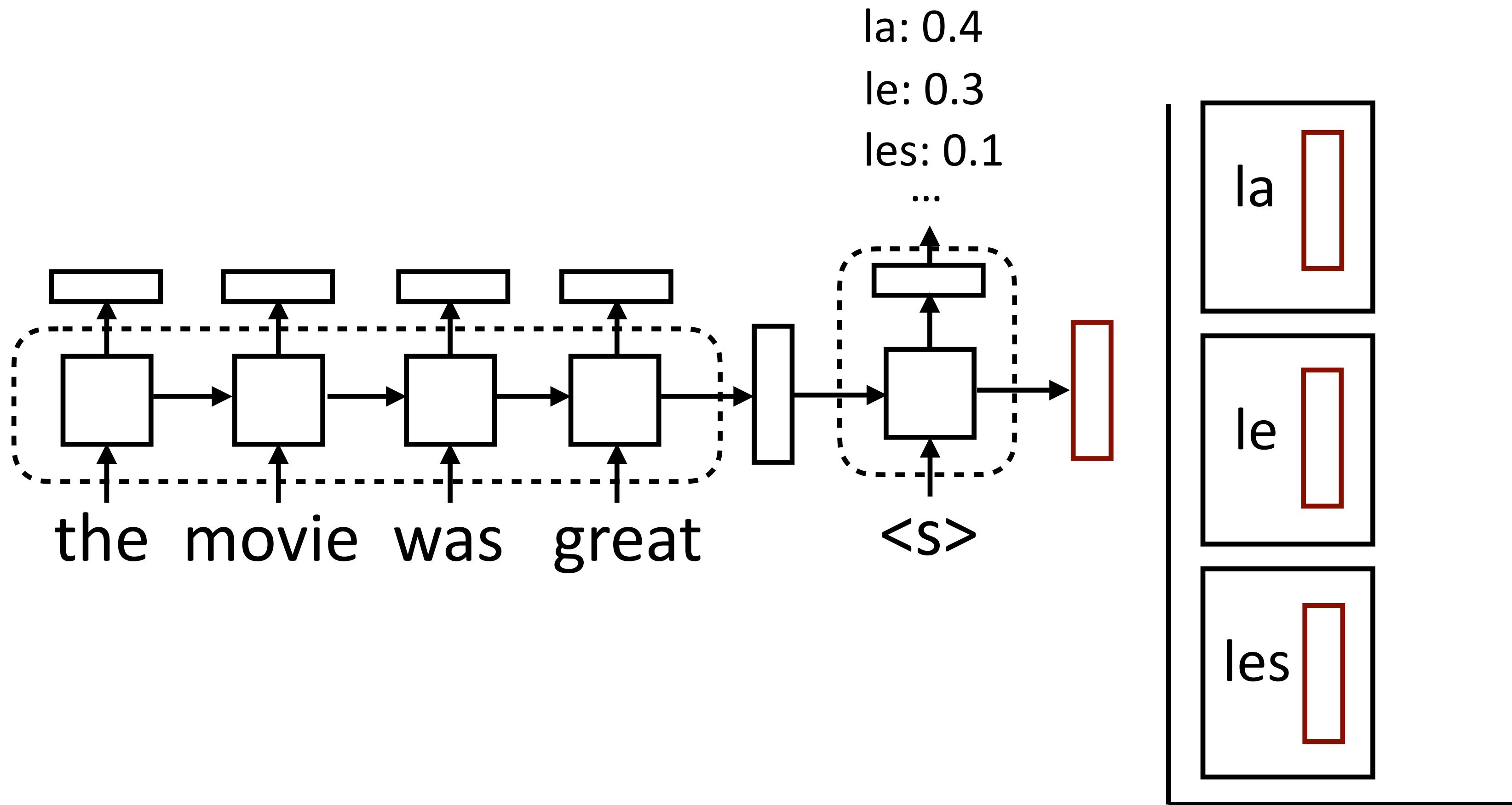
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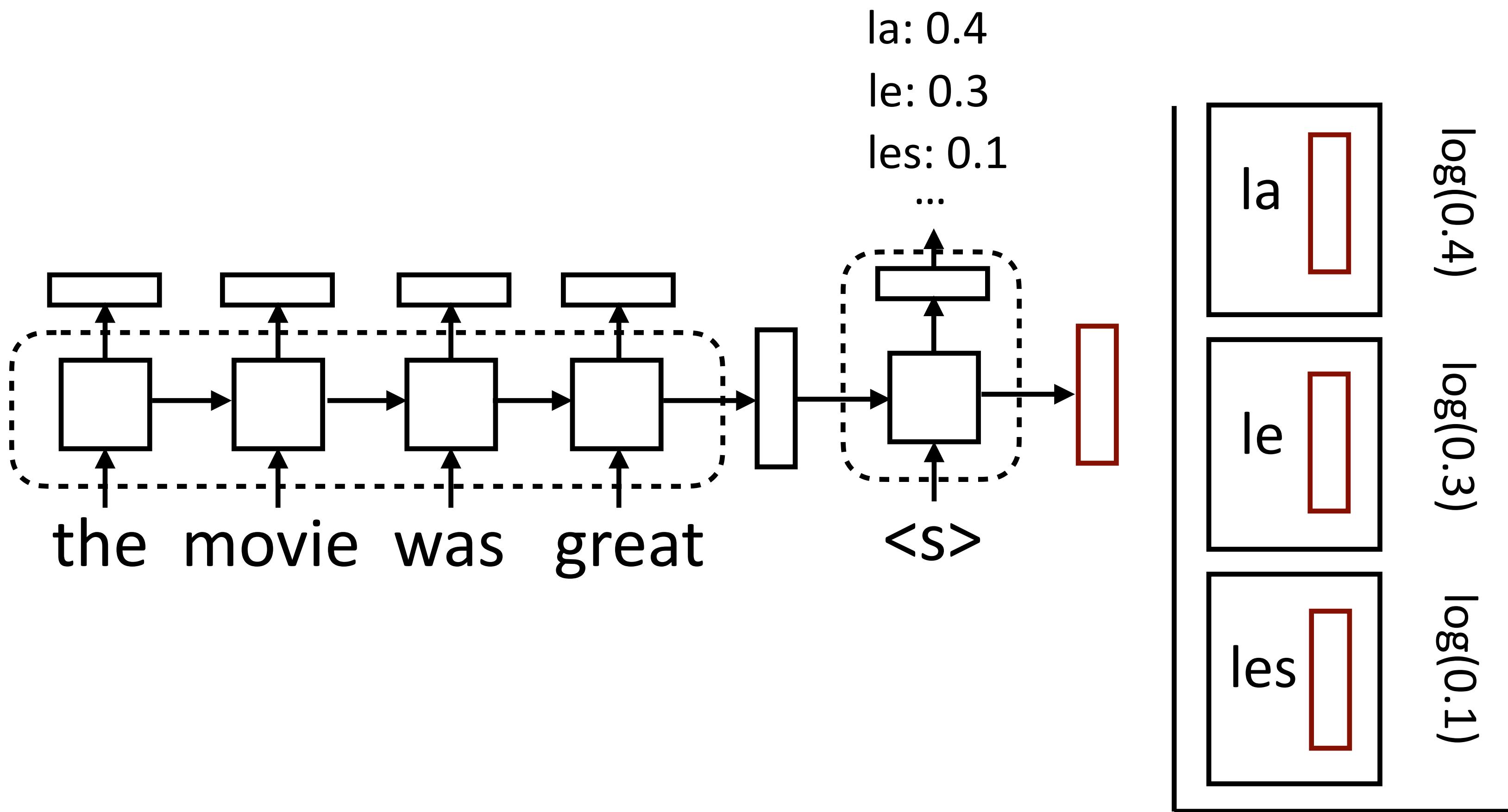
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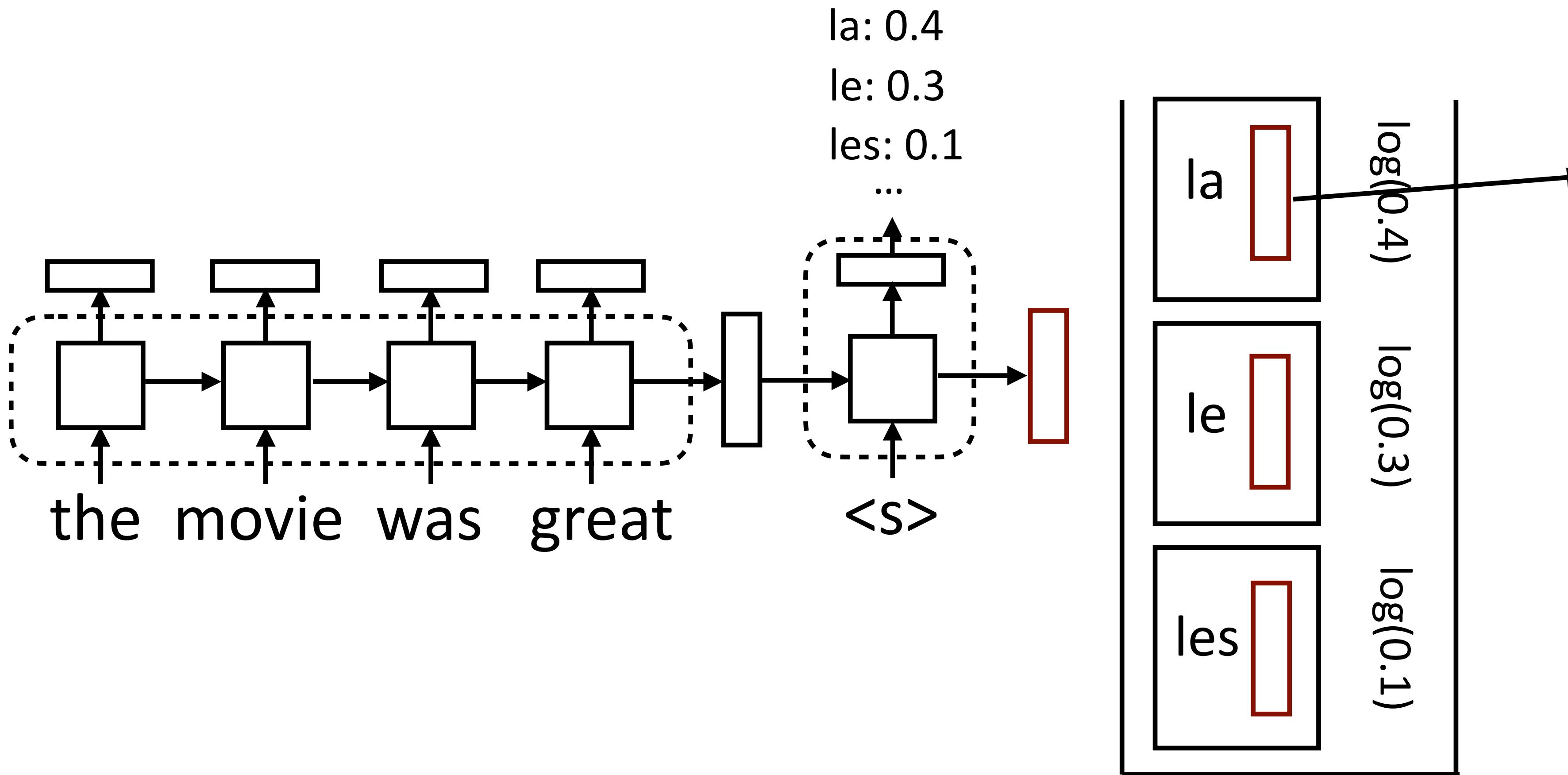
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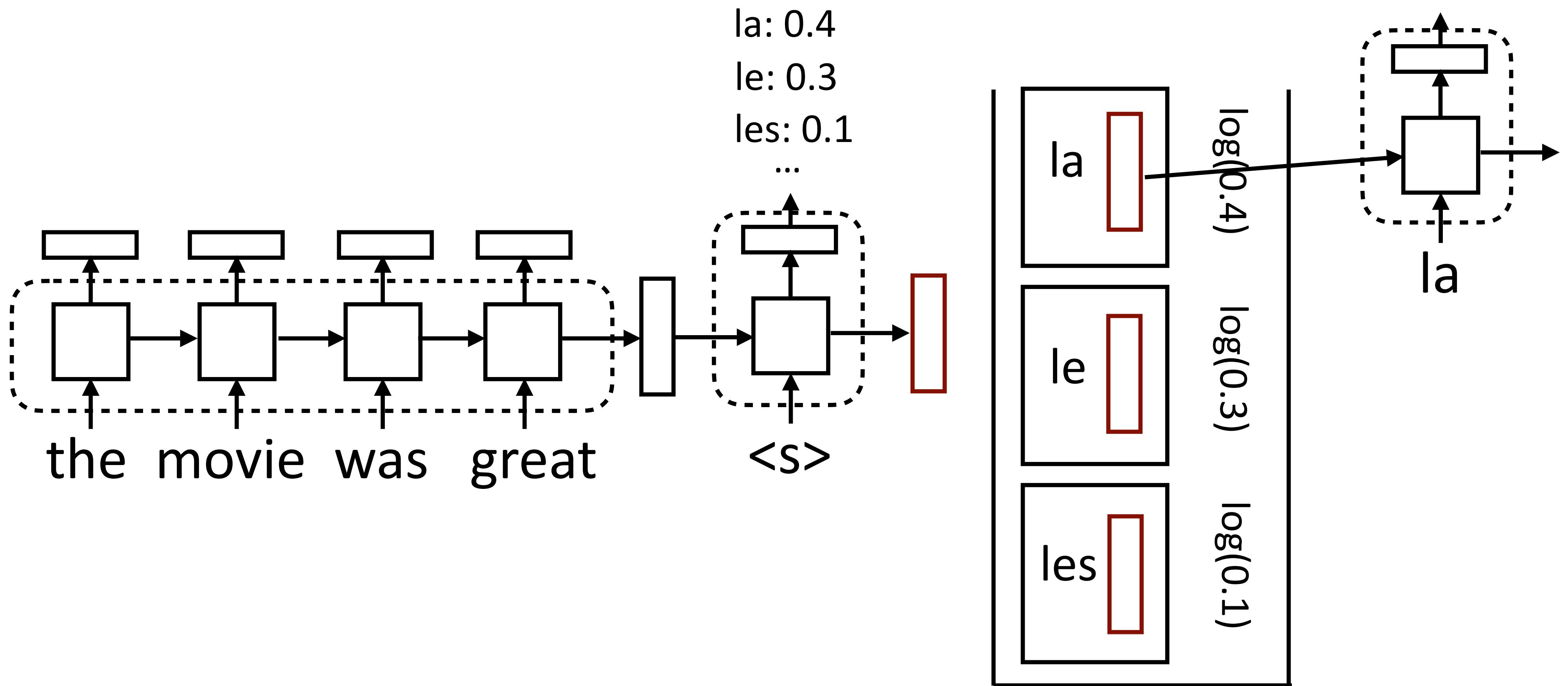
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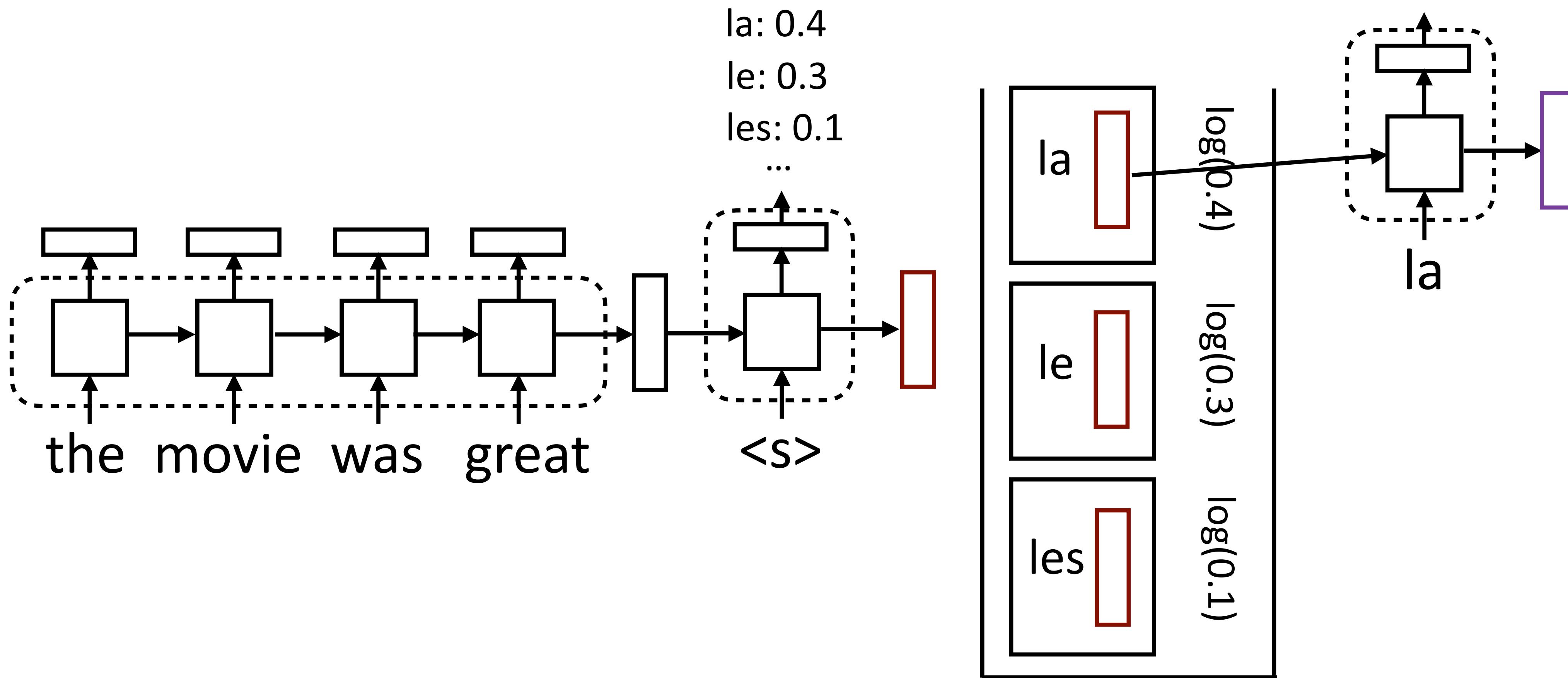
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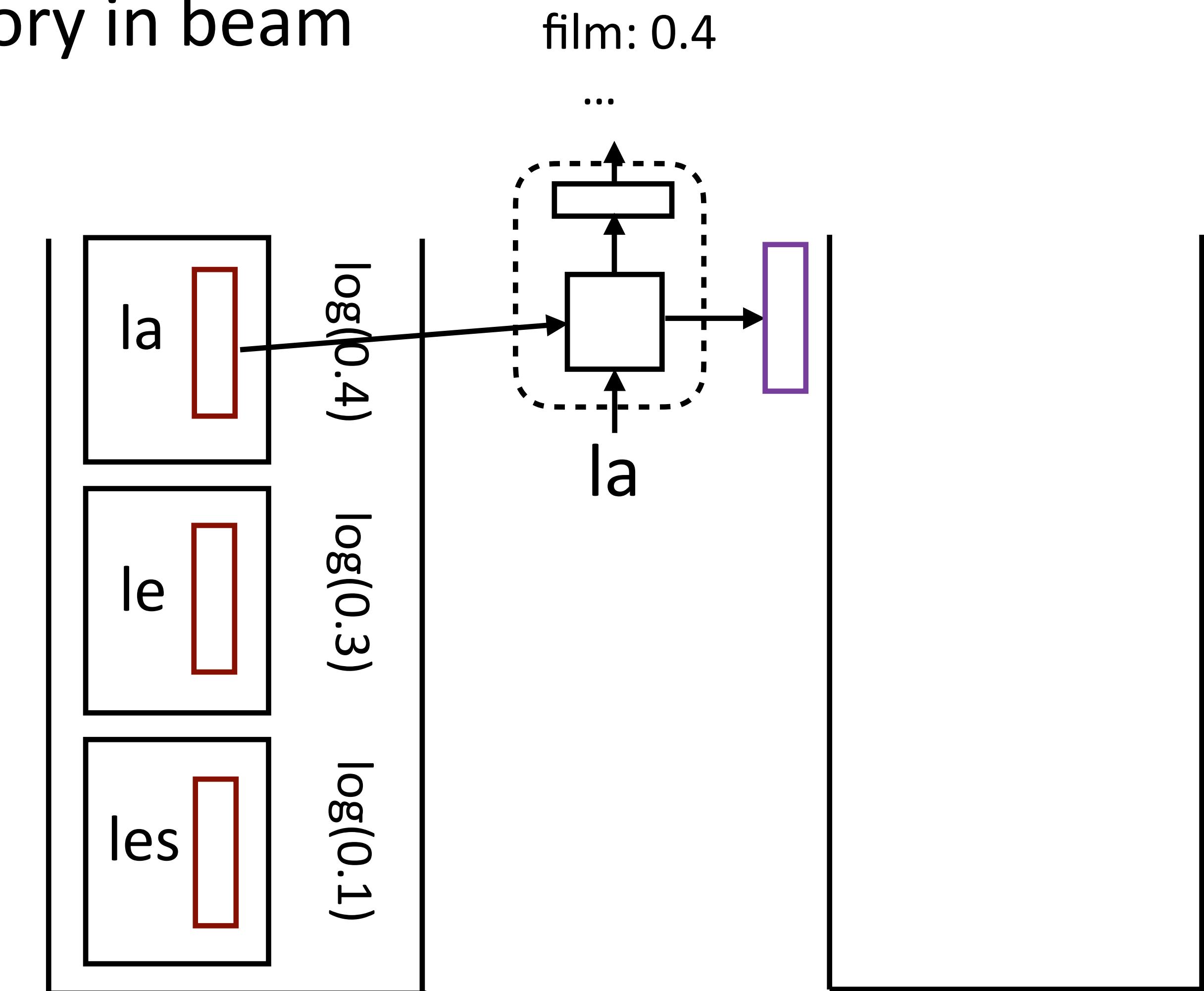
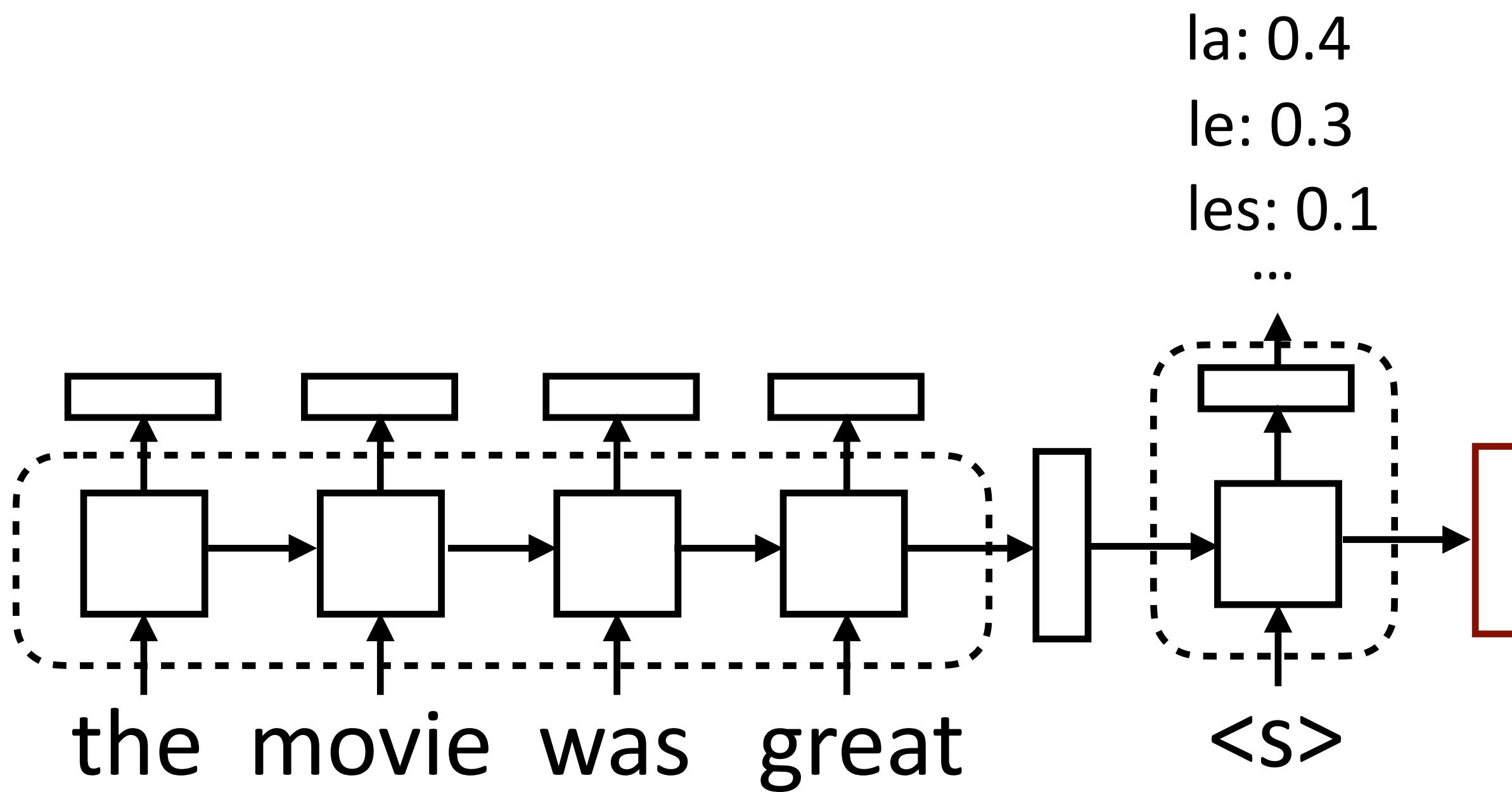
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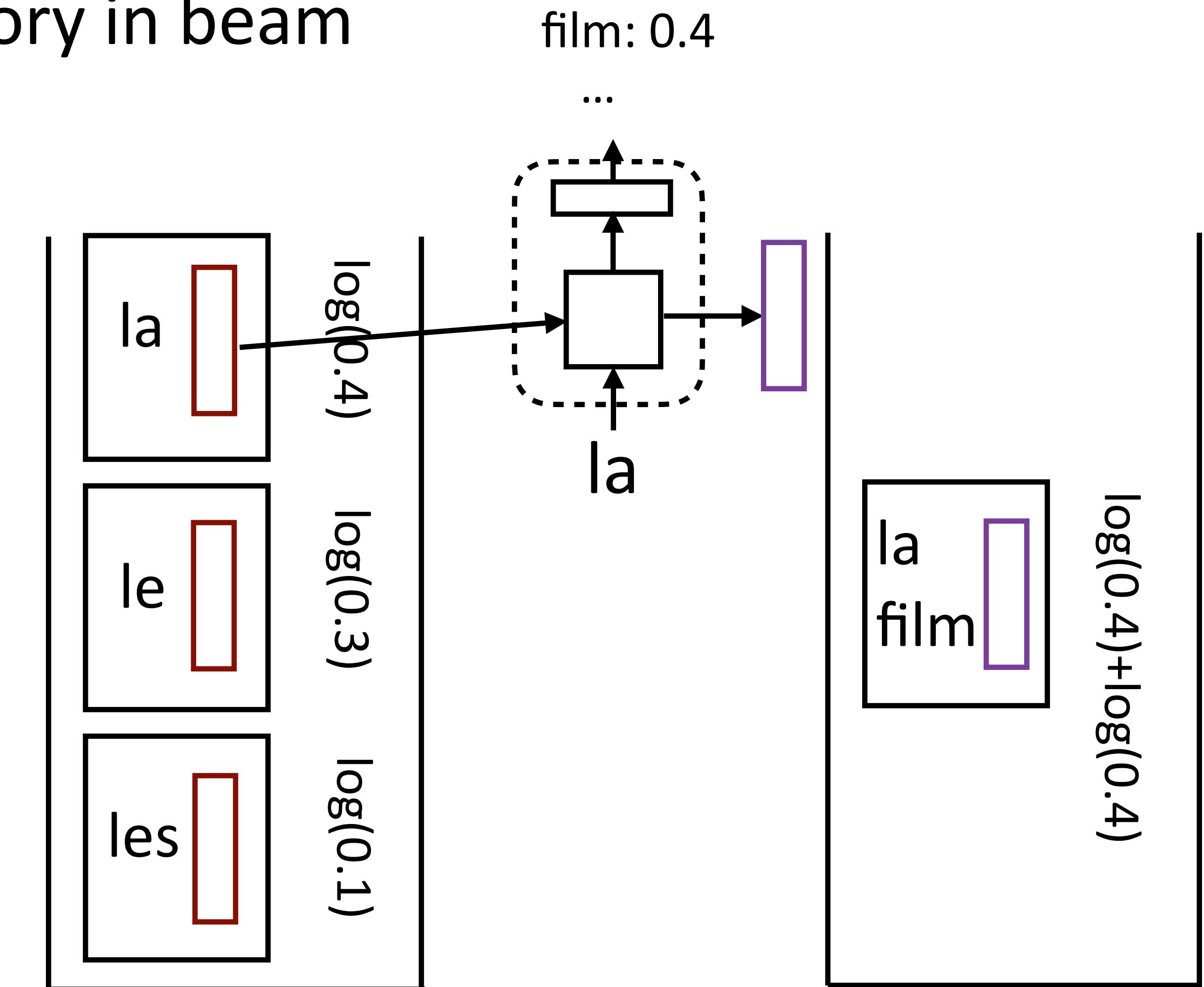
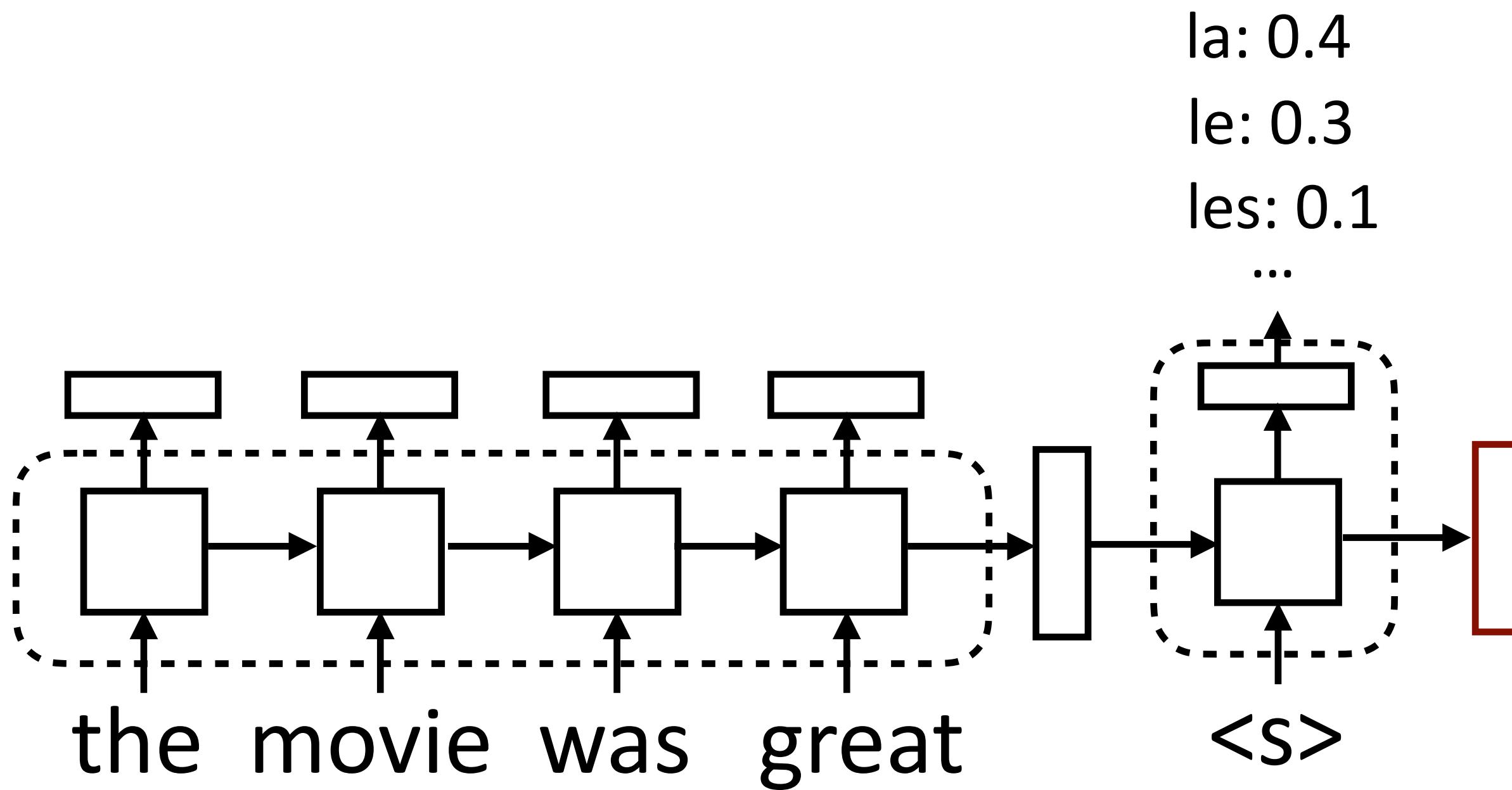
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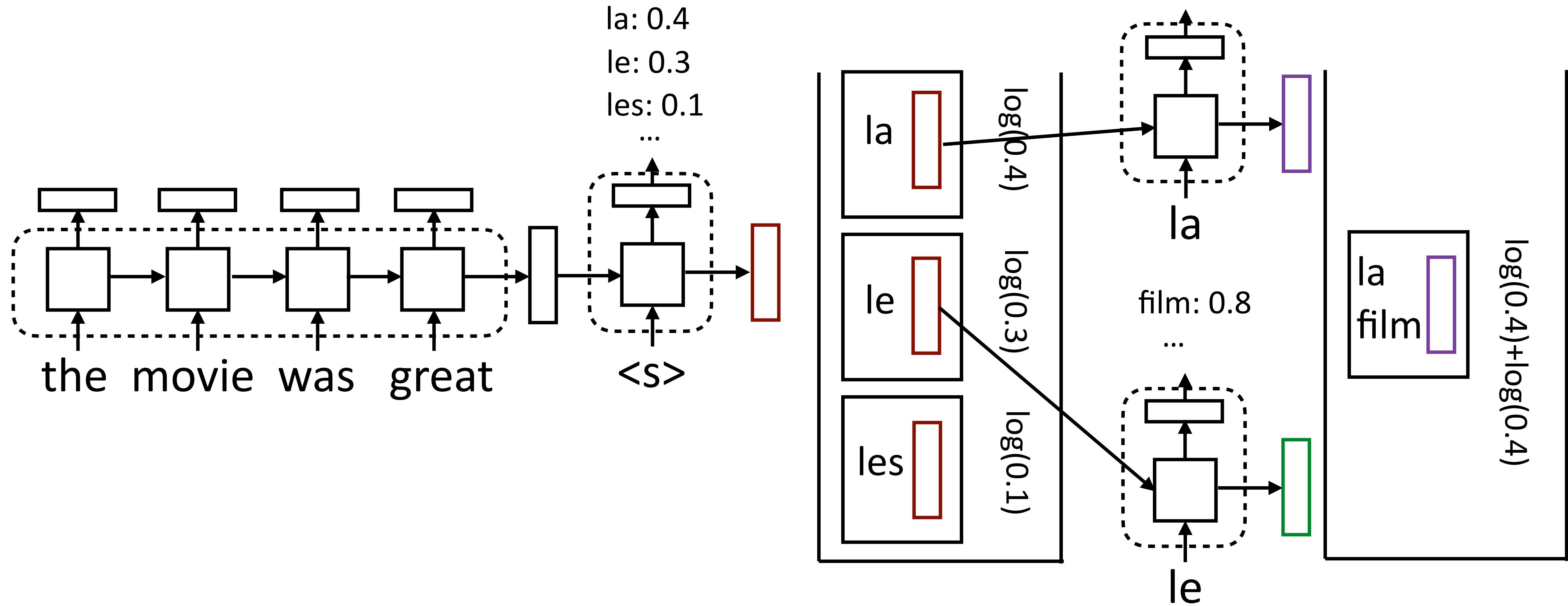
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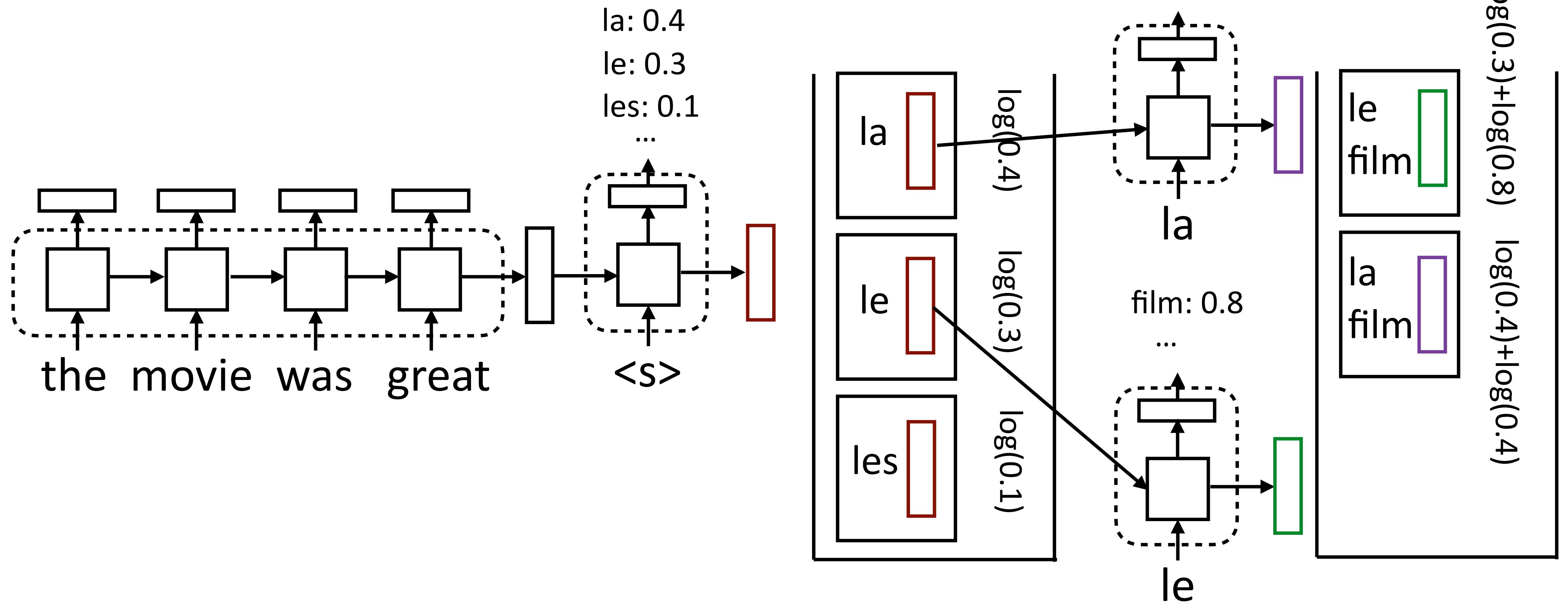
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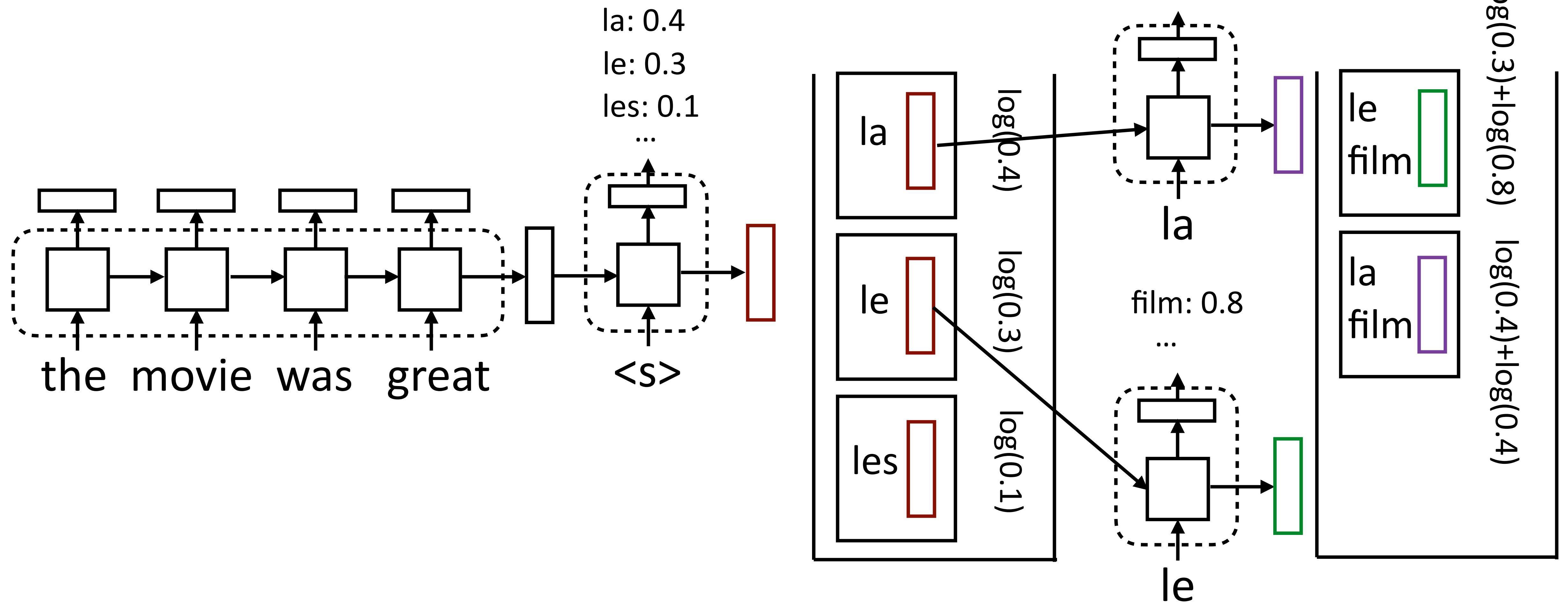
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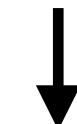
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- Do **not** max over the two *film* states! Hidden state vectors are different

Semantic Parsing as Translation

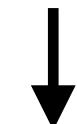
“what states border Texas”



lambda x (state (x) and border (x , e89)))

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- ▶ Might not produce well-formed logical forms, might require lots of data

Regex Prediction

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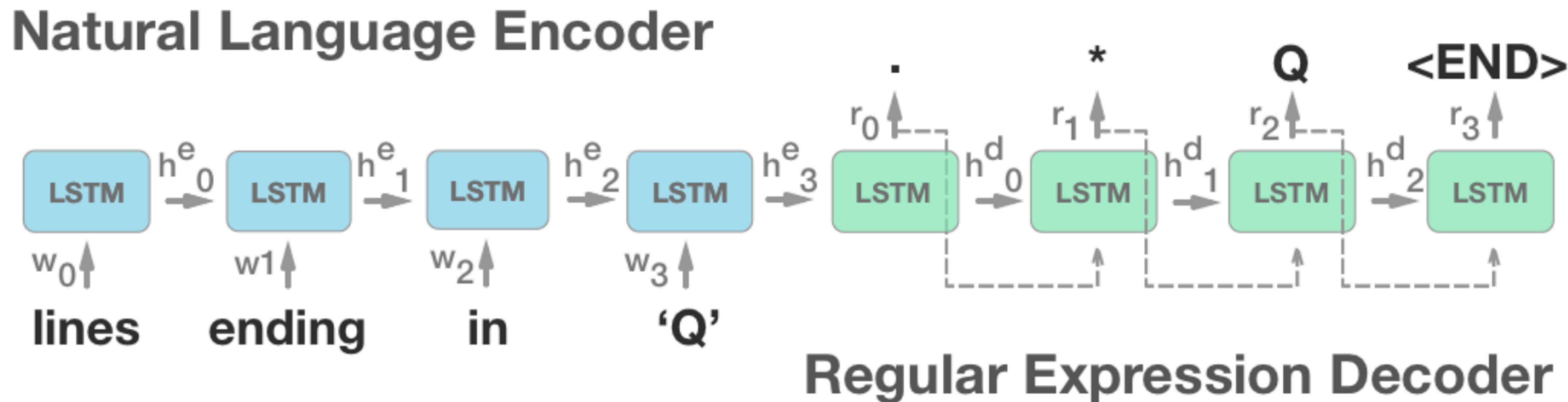
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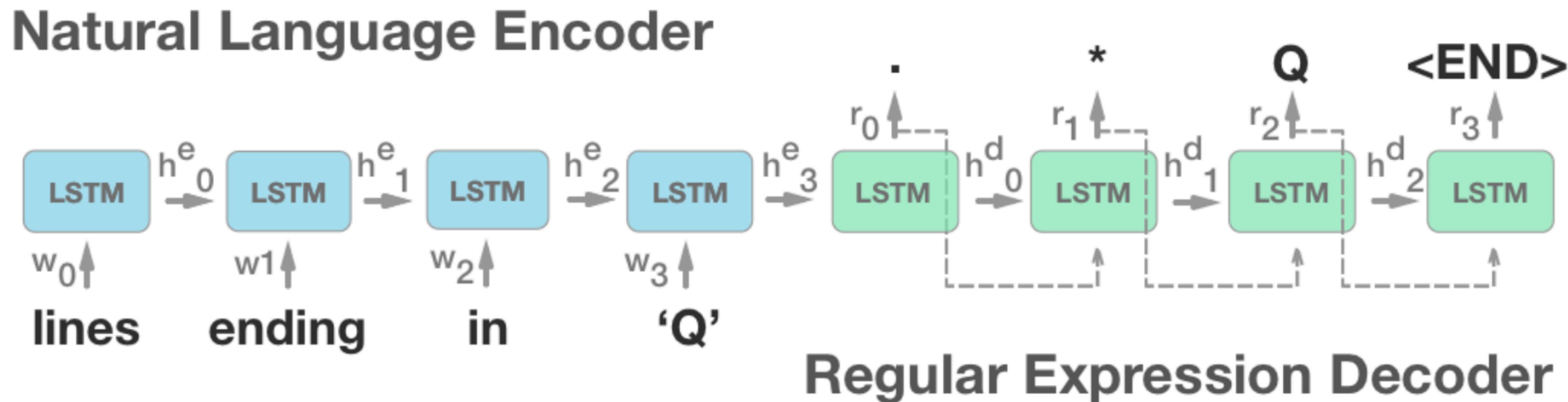
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- ▶ Problem: requires a lot of data: 10,000 examples needed to get ~60% accuracy on pretty simple regexes

SQL Generation

- ▶ Convert natural language description into a SQL query against some DB

Question:

How many CFL teams are from York College?

SQL:

```
SELECT COUNT CFL Team FROM  
CFLDraft WHERE College = "York"
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SQL Generation

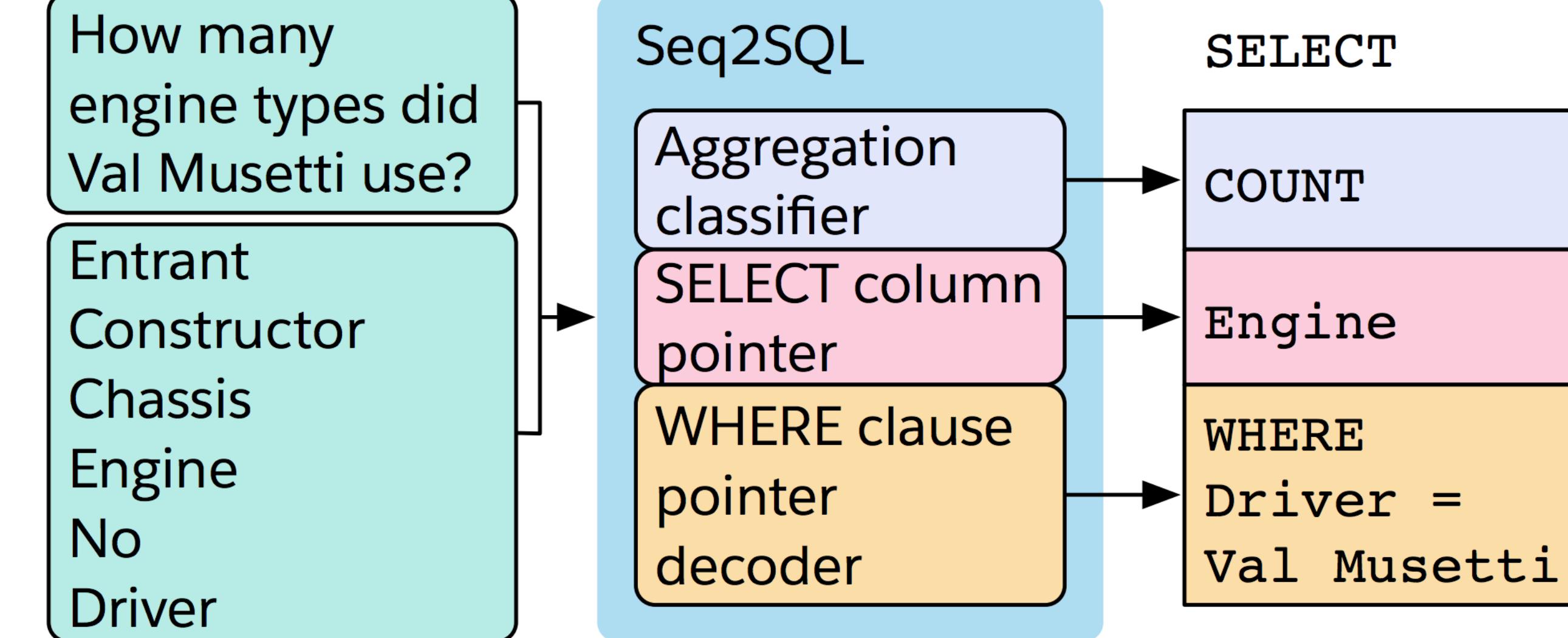
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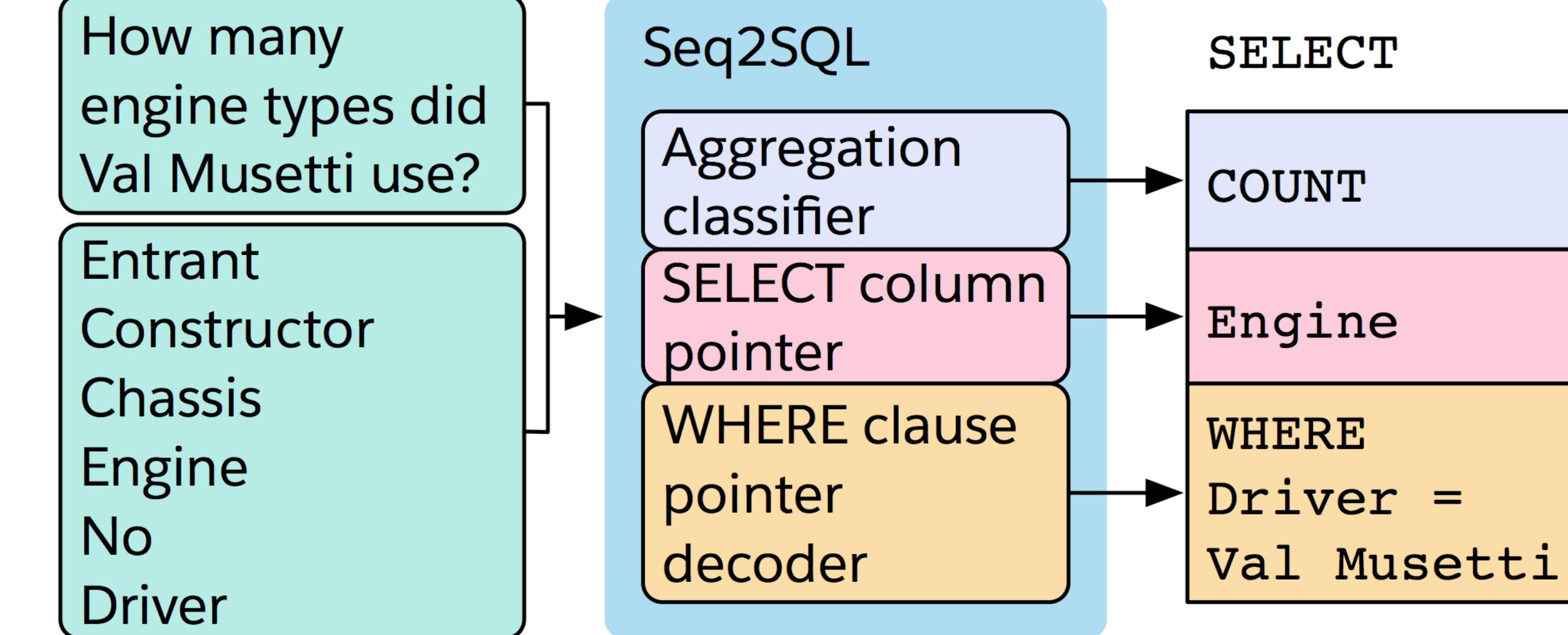
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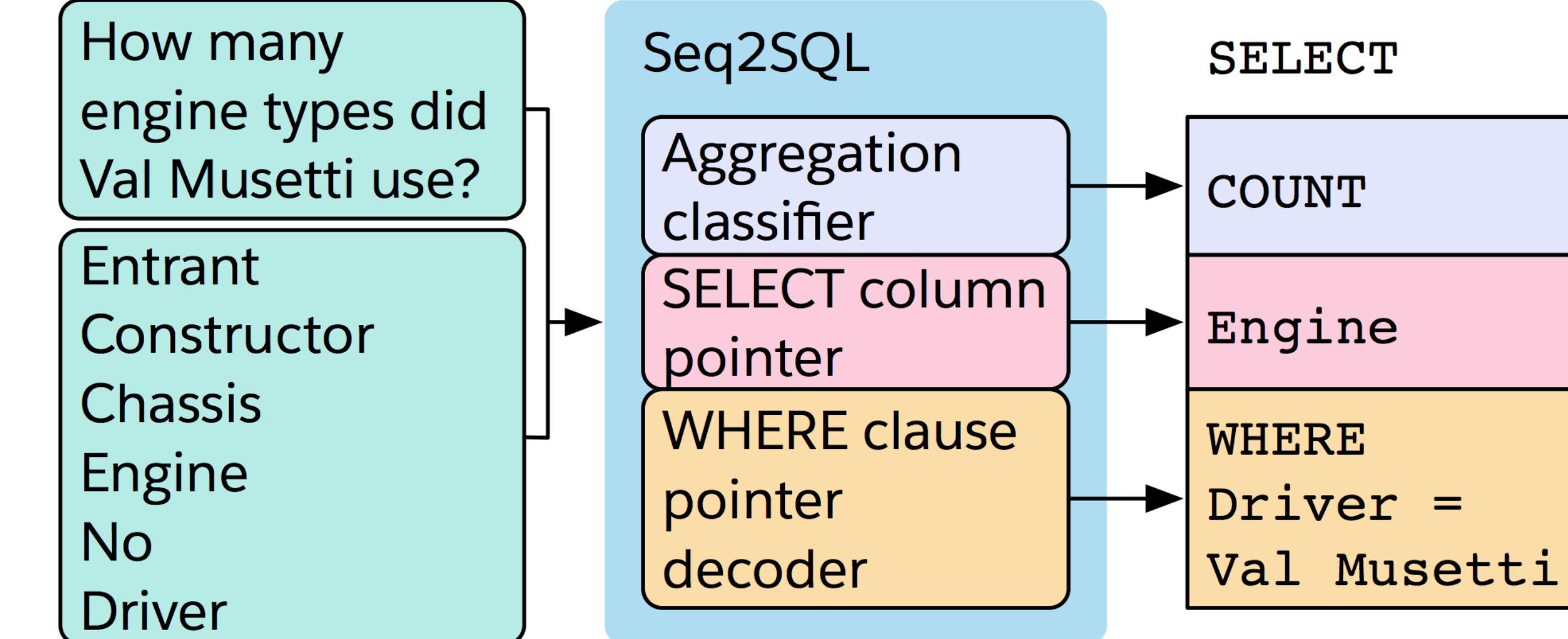
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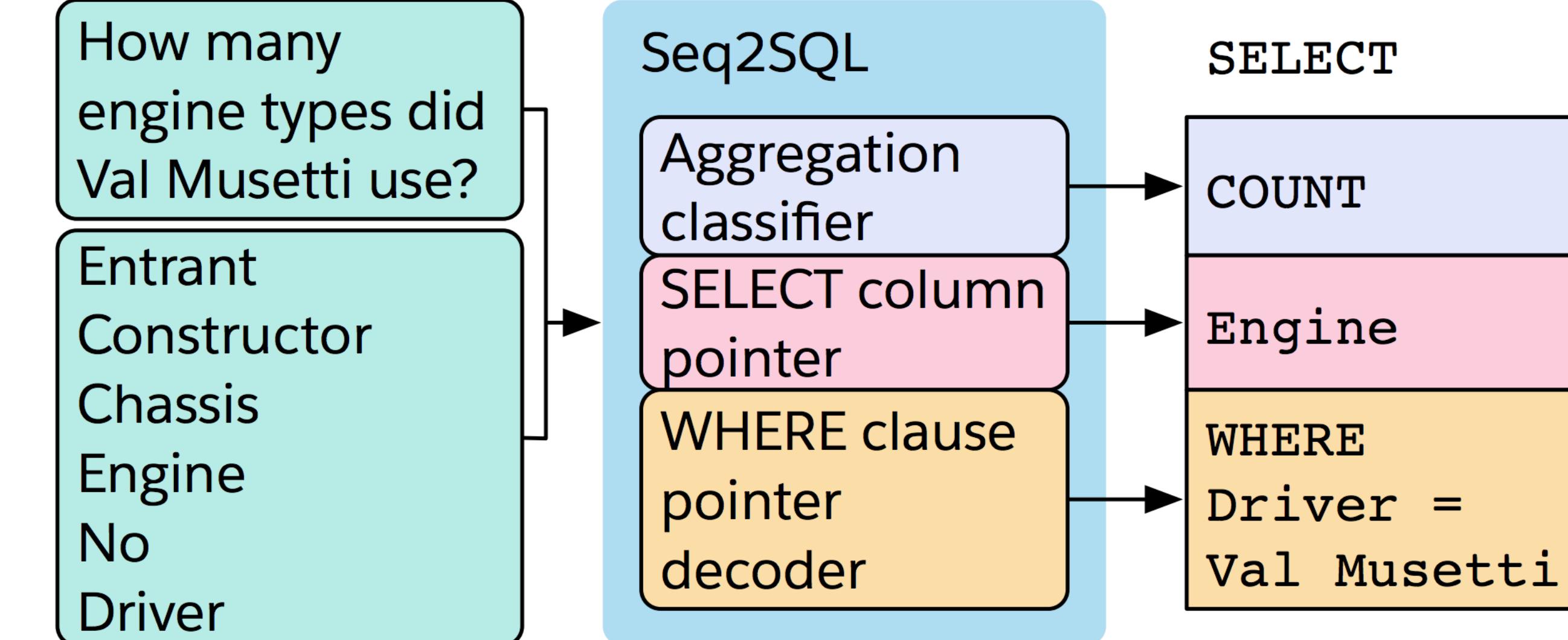
- ▶ Convert natural language description into a SQL query against some DB
- ▶ How to ensure that well-formed SQL is generated?
 - ▶ Three seq2seq models
 - ▶ How to capture column names + constants?

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SQL:

```
SELECT COUNT CFL Team FROM  
CFLDraft WHERE College = "York"
```



SQL Generation

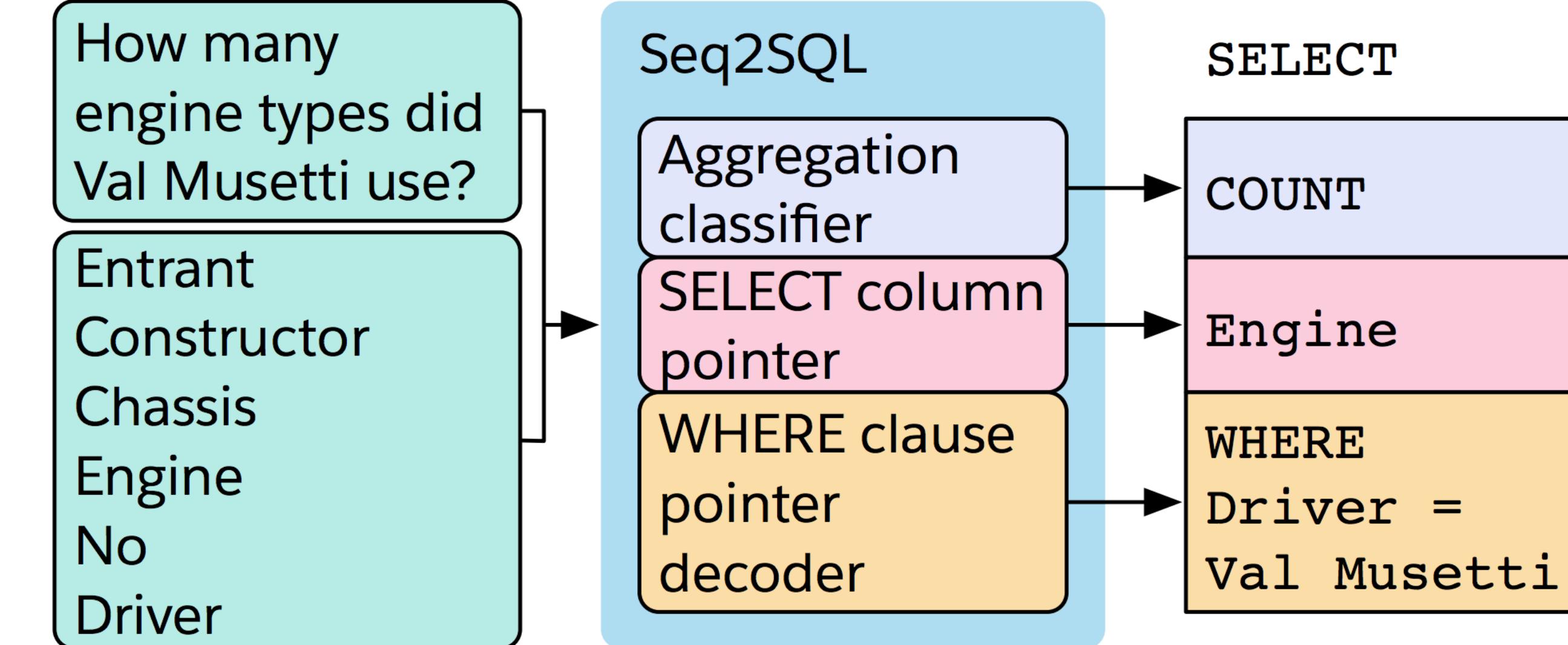
- ▶ Convert natural language description into a SQL query against some DB
- ▶ How to ensure that well-formed SQL is generated?
 - ▶ Three seq2seq models
 - ▶ How to capture column names + constants?
 - ▶ Pointer mechanisms

Question:

How many CFL teams are from York College?

SQL:

```
SELECT COUNT CFL Team FROM  
CFLDraft WHERE College = "York"
```



Attention

Problems with Seq2seq Models

- ▶ Encoder-decoder models like to repeat themselves:

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Un garçon joue dans la neige → A boy plays in the snow **boy plays boy plays**

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Un garçon joue dans la neige → A boy plays in the snow **boy plays boy plays**

- ▶ Often a byproduct of training these models poorly
- ▶ Need some notion of input coverage or what input words we've translated

Problems with Seq2seq Models

- ▶ Unknown words:

en: The ecotax portico in Pont-de-Buis , ... [truncated] ..., was taken down on Thursday morning

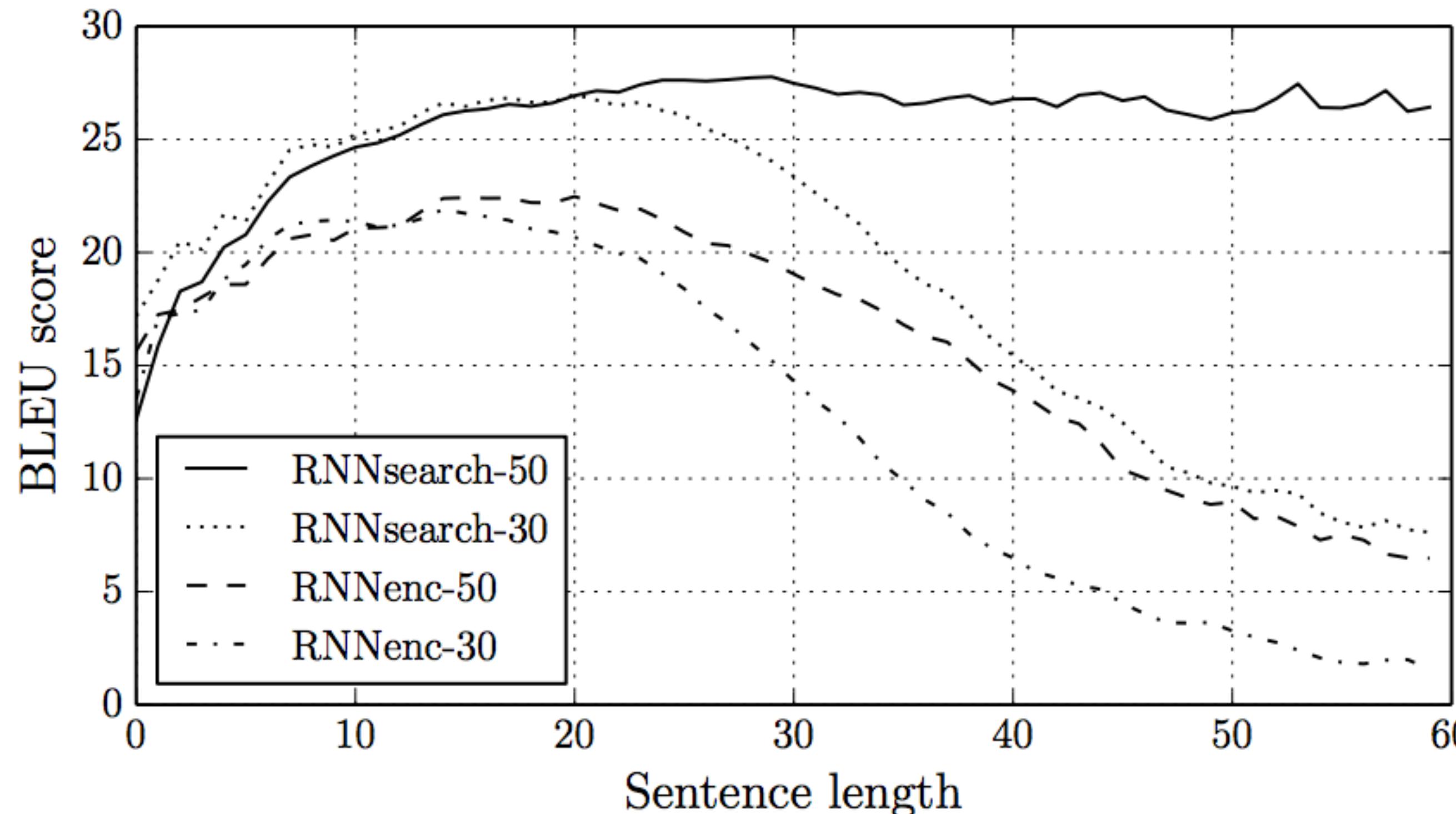
fr: Le portique écotaxe de Pont-de-Buis , ... [truncated] ..., a été démonté jeudi matin

nn: Le unk de unk à unk , ... [truncated] ..., a été pris le jeudi matin

- ▶ No matter how much data you have, you'll need some mechanism to copy a word like Pont-de-Buis from the source to target

Problems with Seq2seq Models

- ▶ Bad at long sentences: 1) a fixed-size representation doesn't scale; 2) LSTMs still have a hard time remembering for really long periods of time



RNNsearch: introduces attention mechanism to give “variable-sized” representation

Aligned Inputs

- ▶ Suppose we knew the source and target would be word-by-word translated

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the movie was great

A diagram illustrating word alignment between two sentences. The top sentence is "the movie was great" and the bottom sentence is "le film était bon". Four diagonal lines connect the words: "the" to "le", "movie" to "film", "was" to "était", and "great" to "bon".

the movie was great

| / / /

le film était bon

Aligned Inputs

- ▶ Suppose we knew the source and target would be word-by-word translated

the movie was great
| / / /
le film était bon

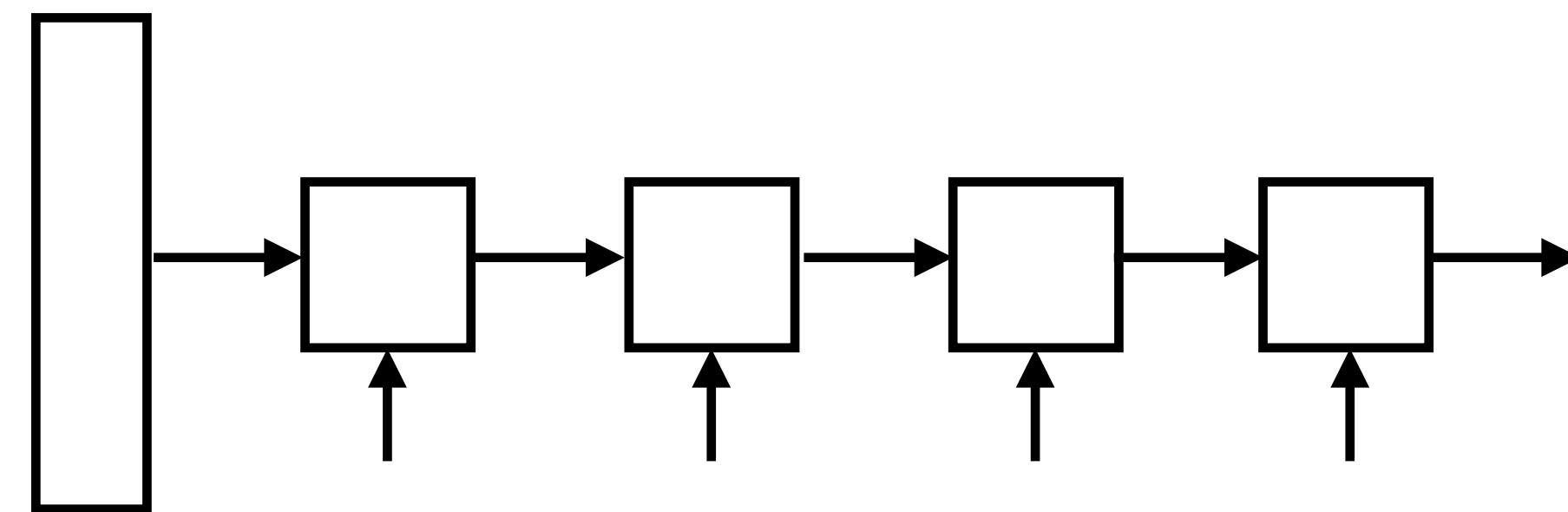
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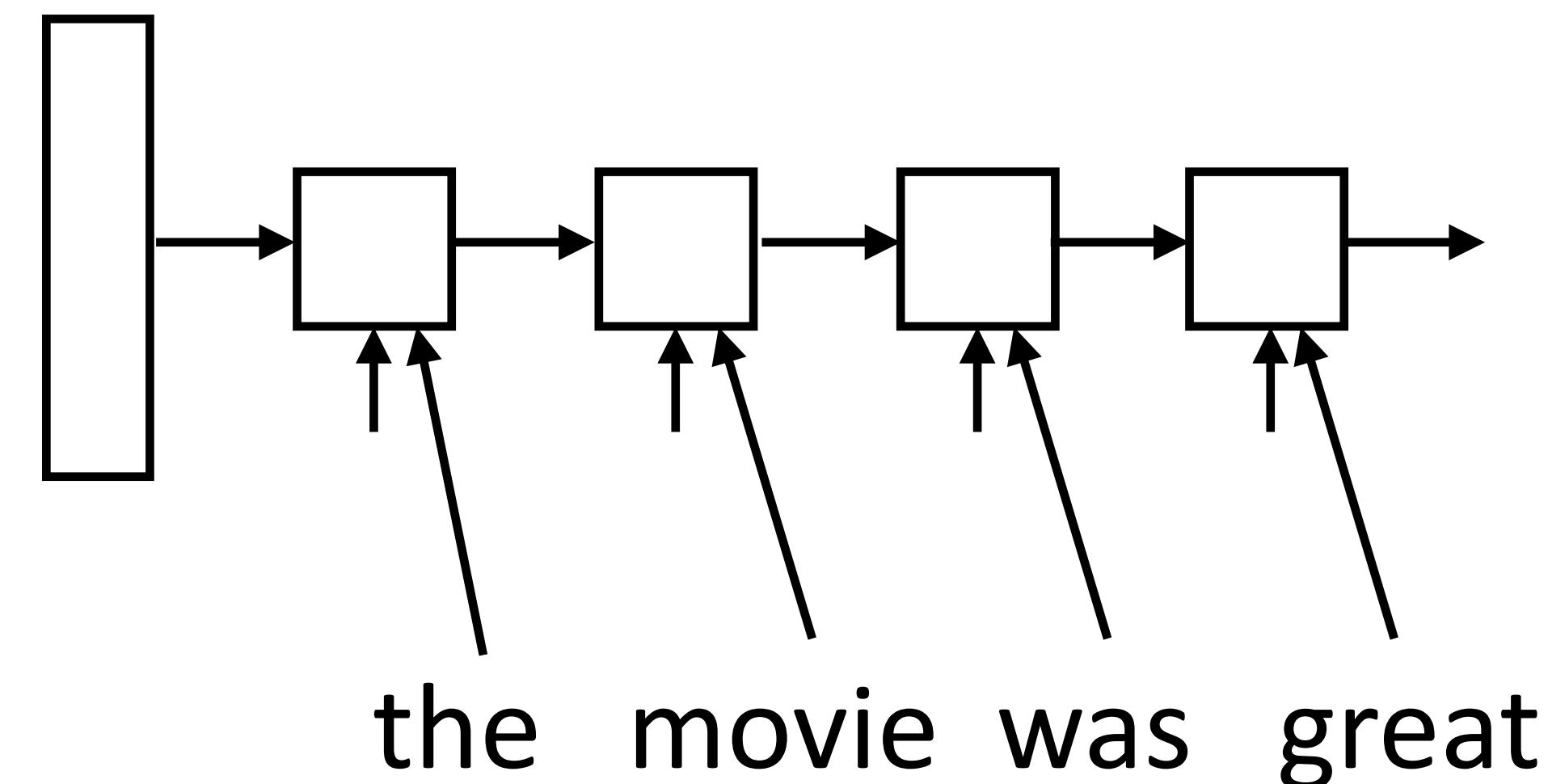


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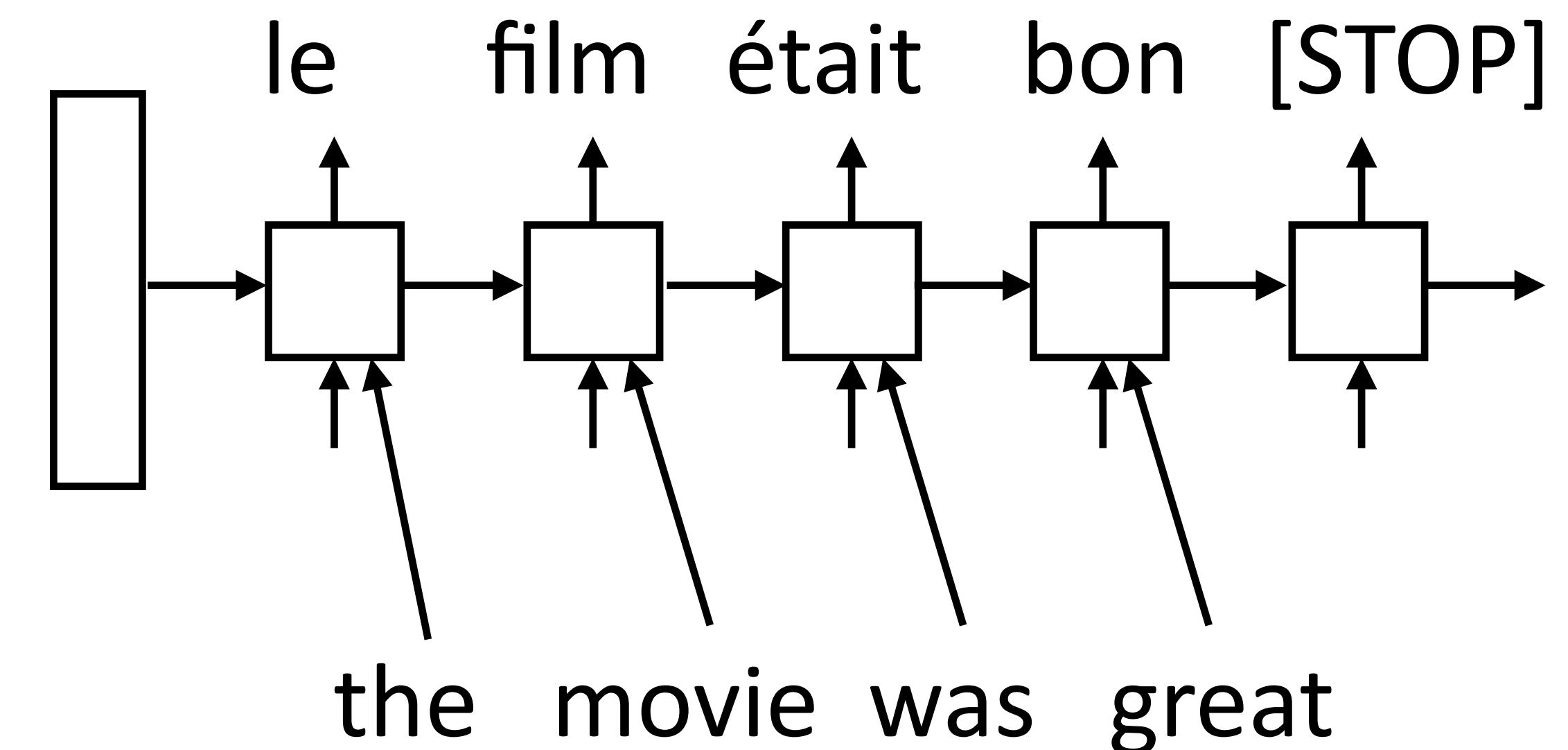


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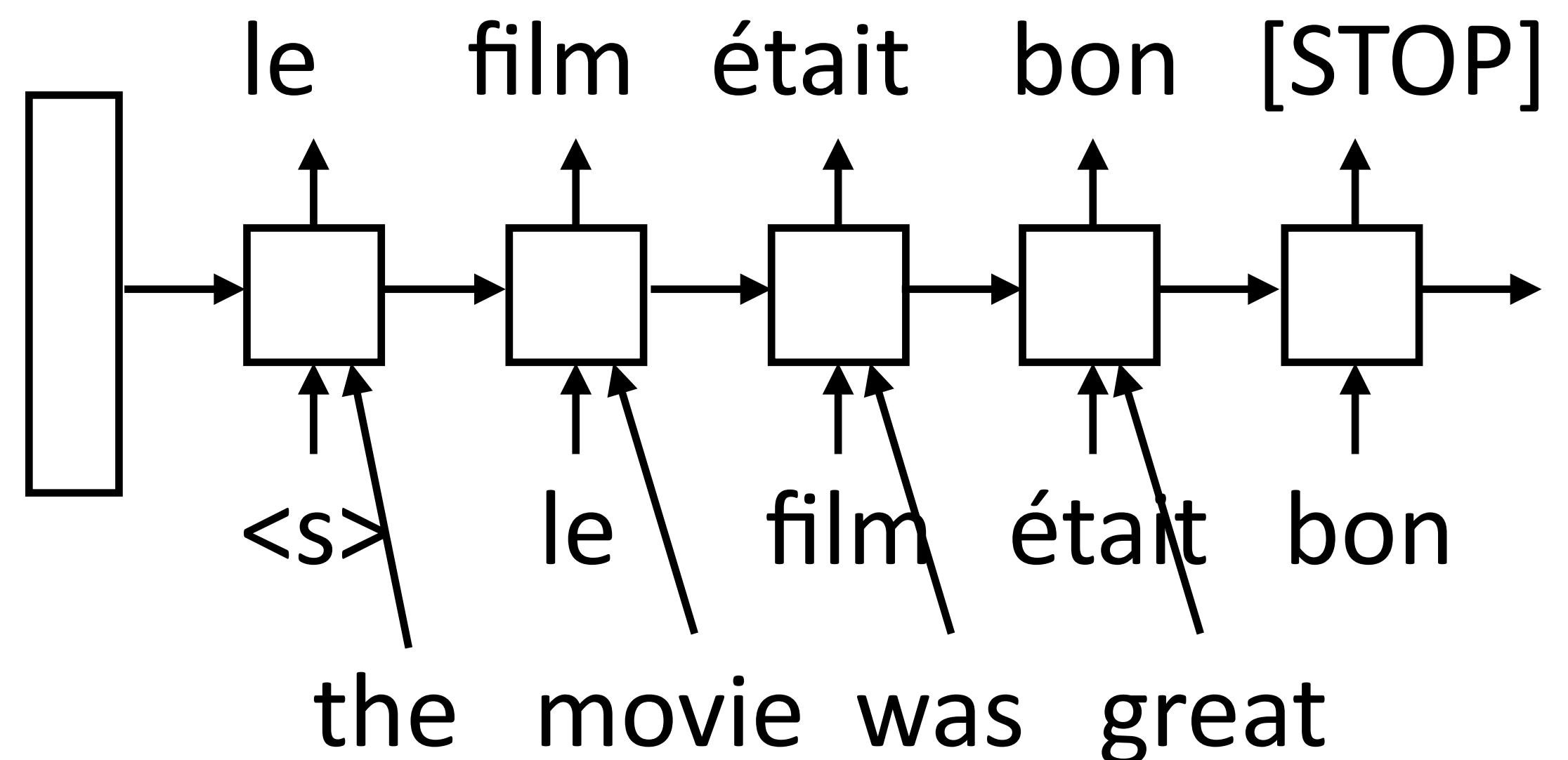


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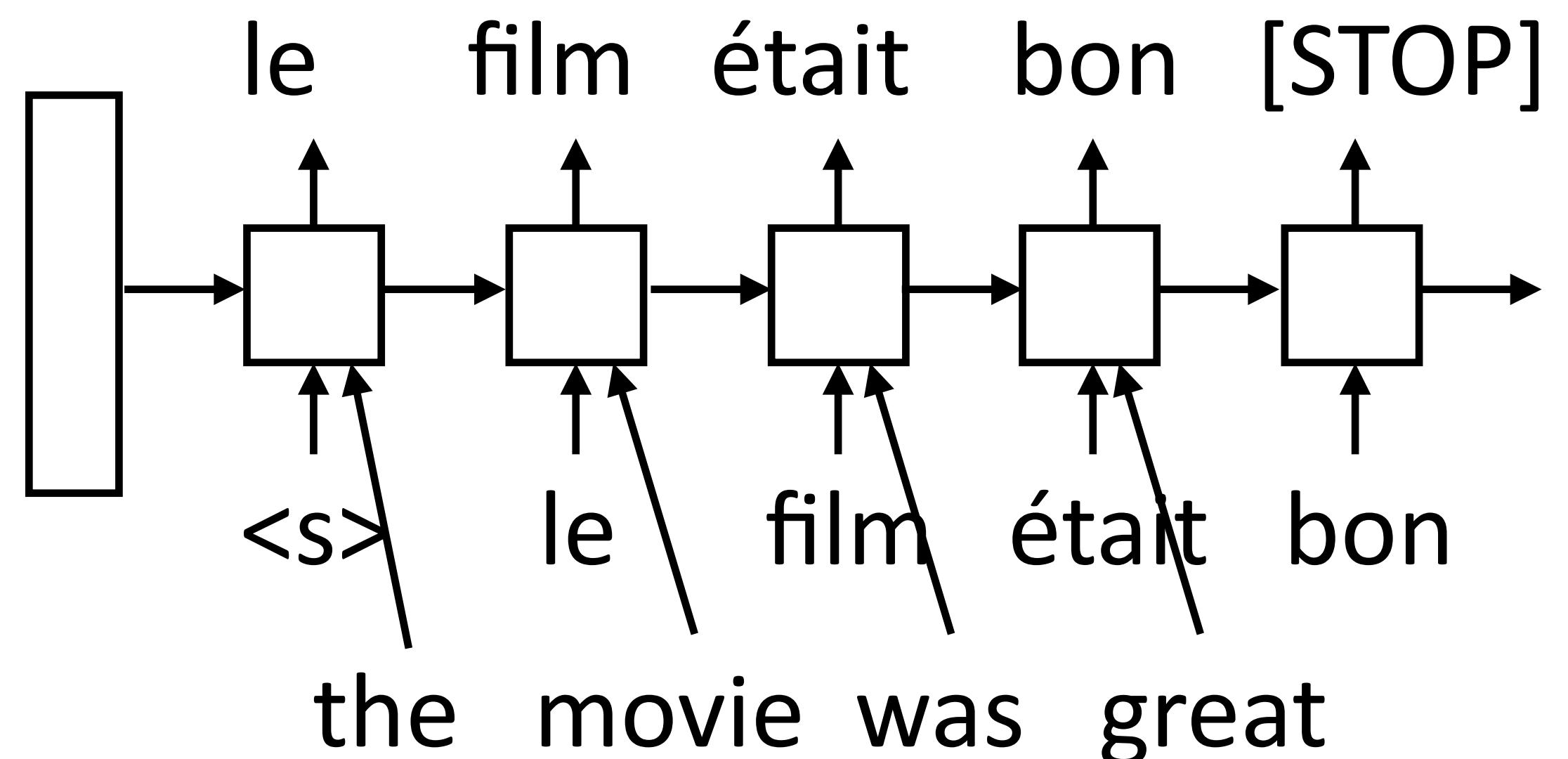
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- ▶ Suppose we knew the source and target would be word-by-word translated

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- ▶ Much less burden on the hidden state



Aligned Inputs

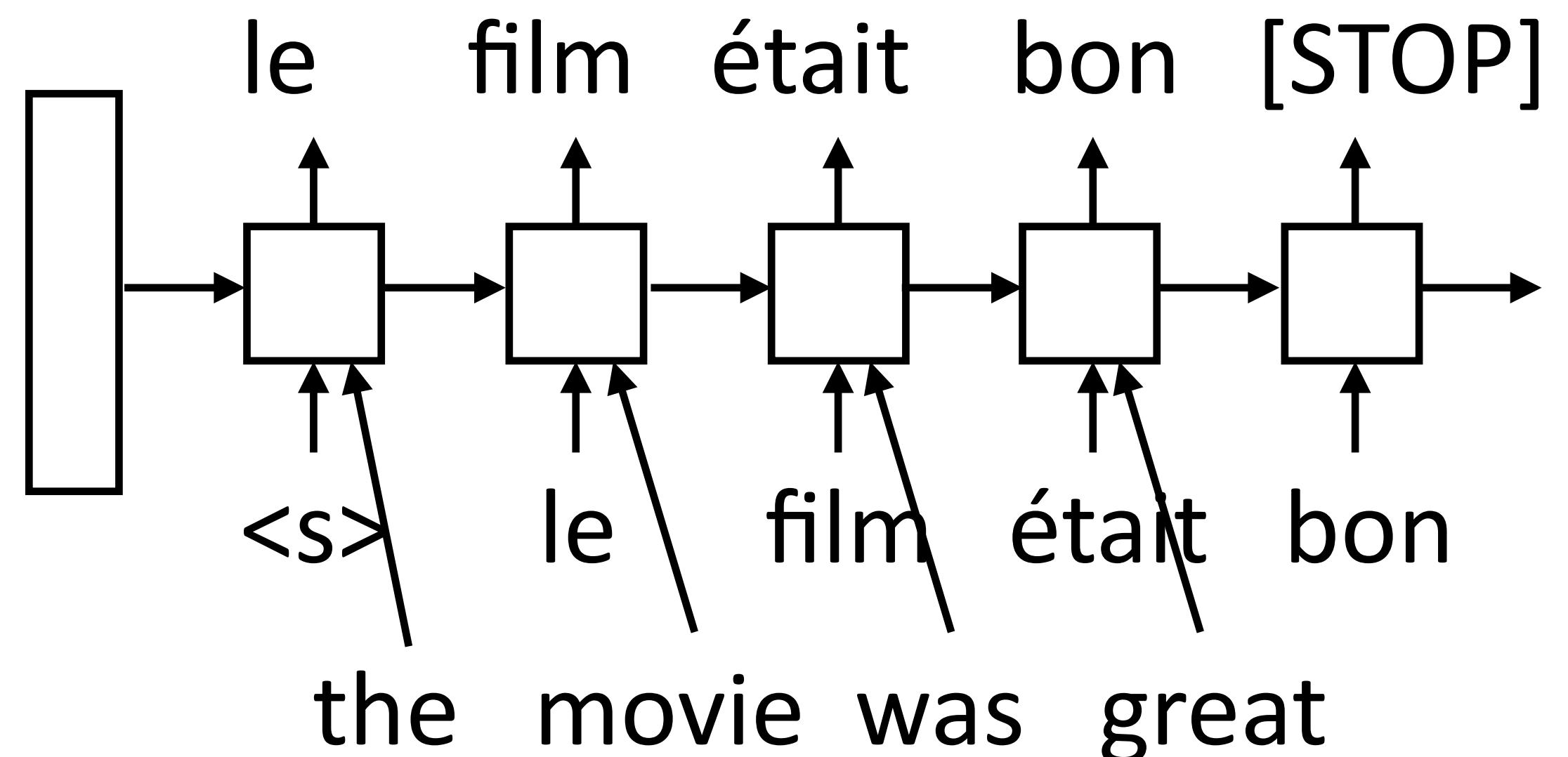
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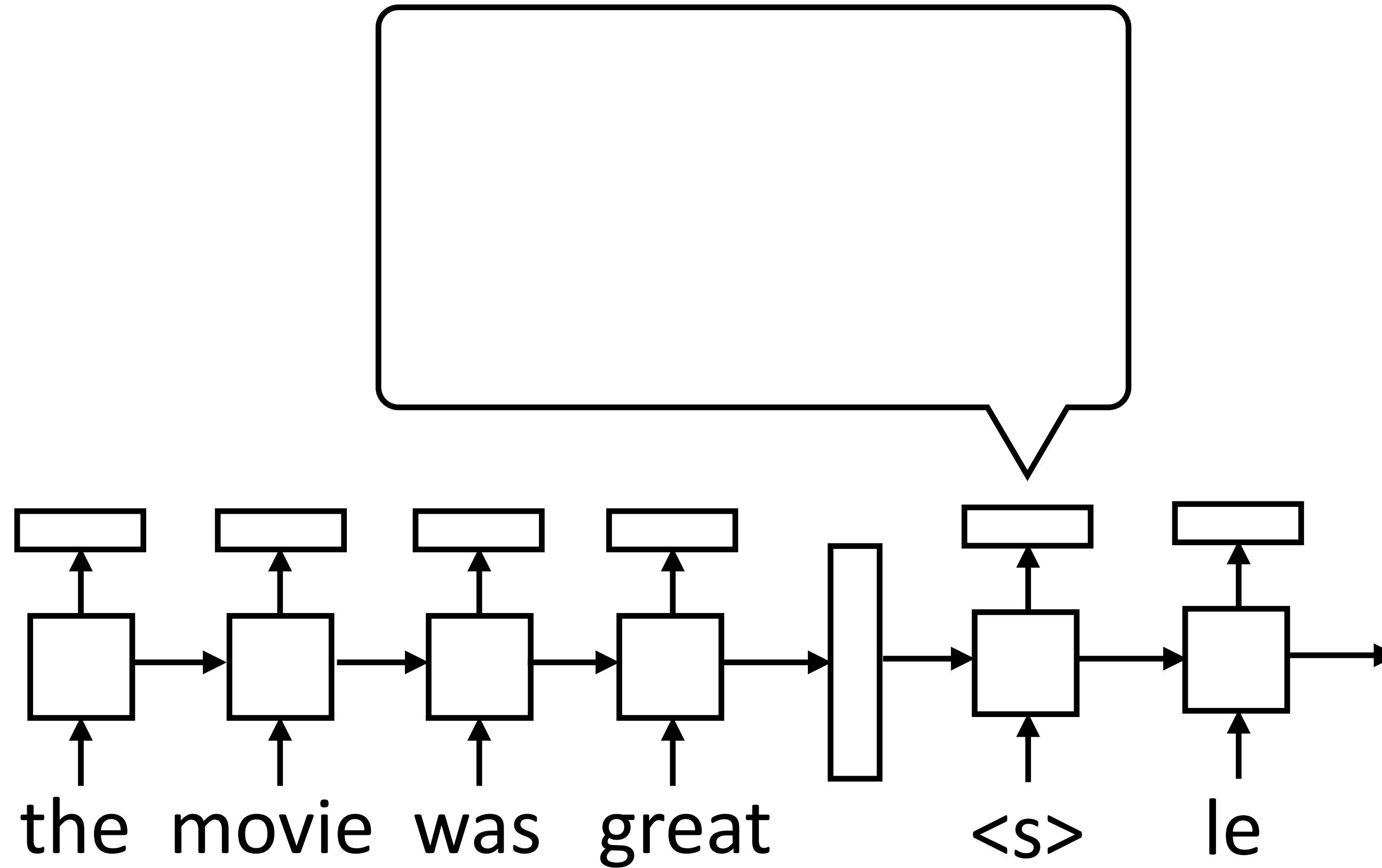
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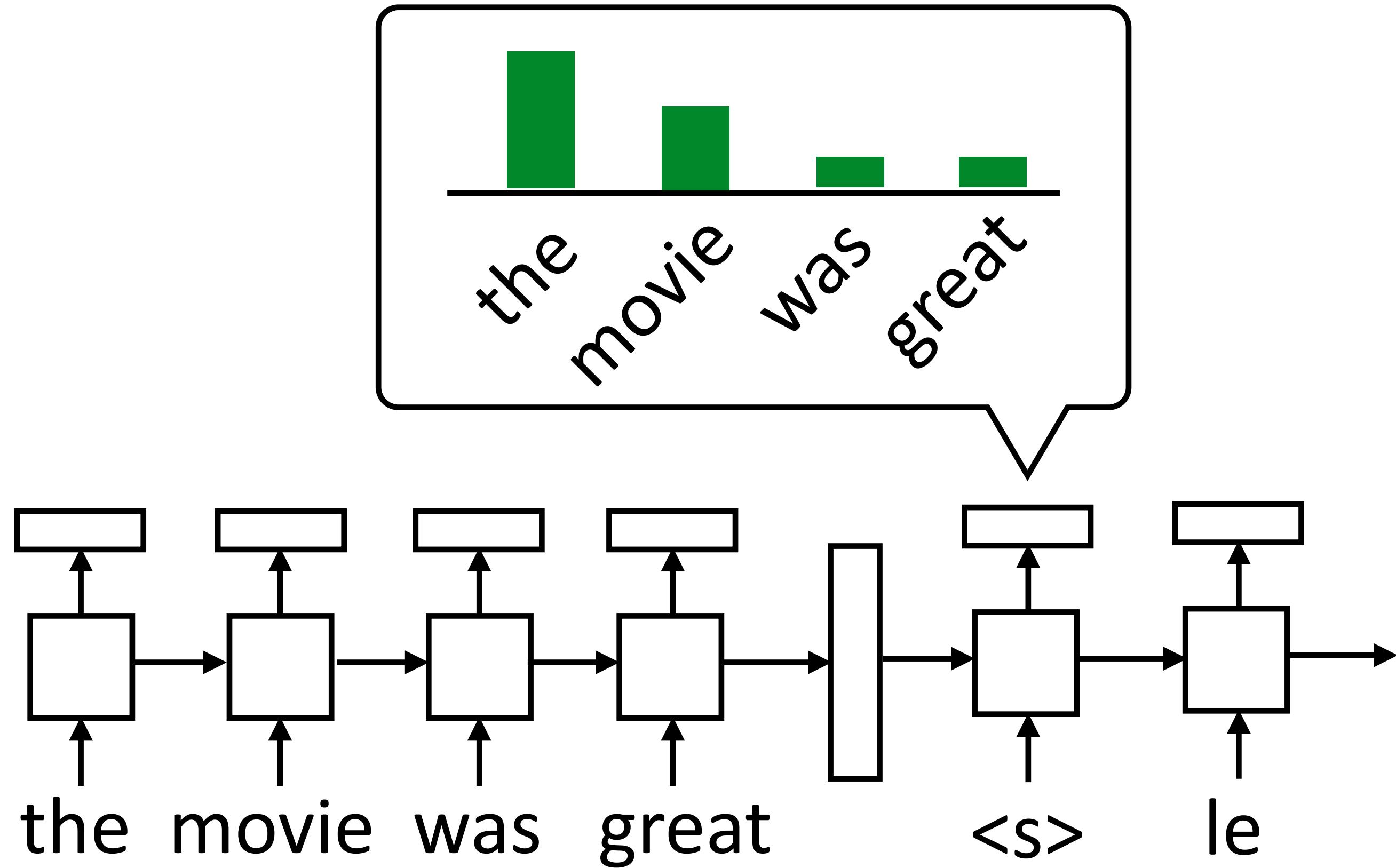
- ▶ How can we achieve this without hardcoding it?



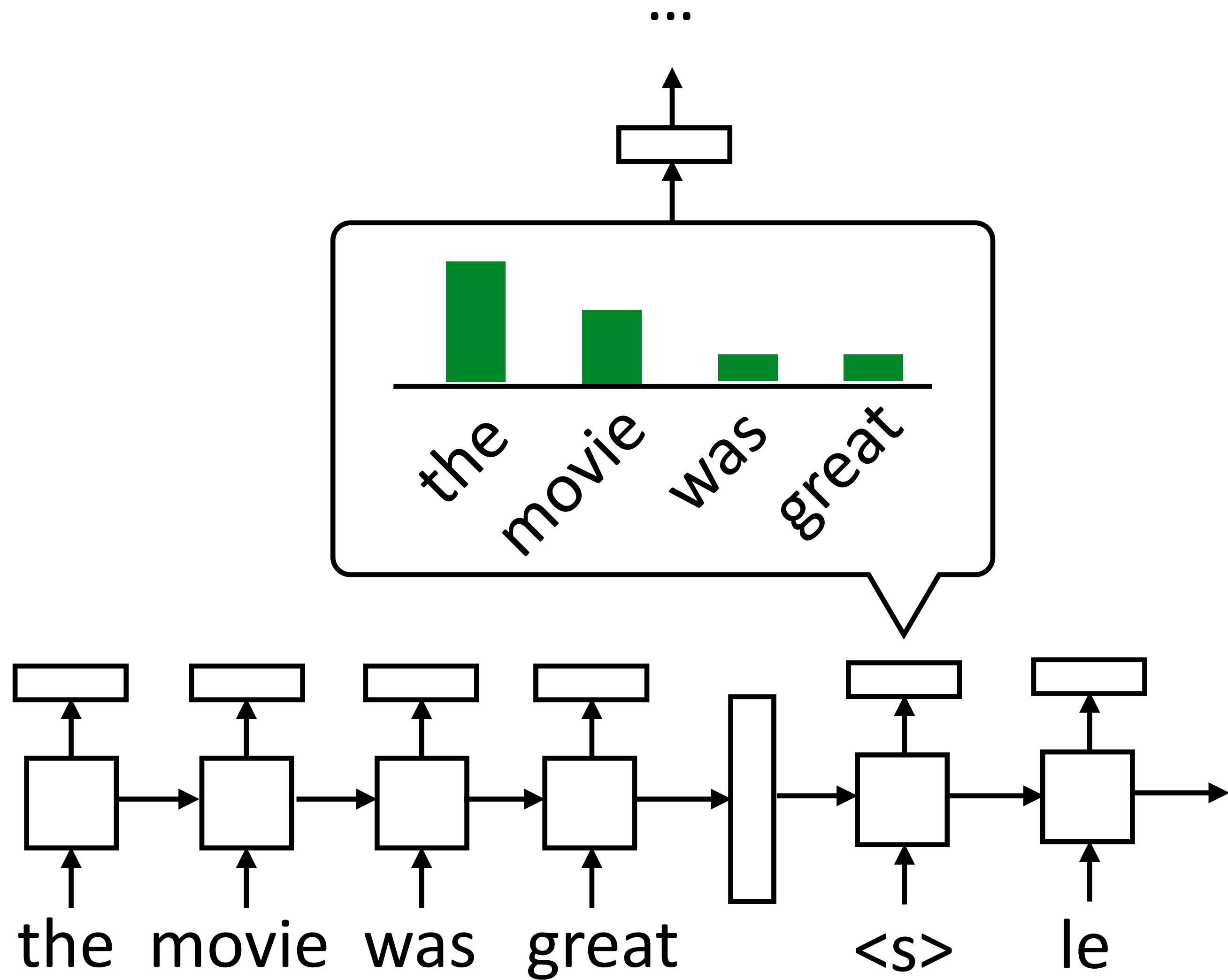
Attention



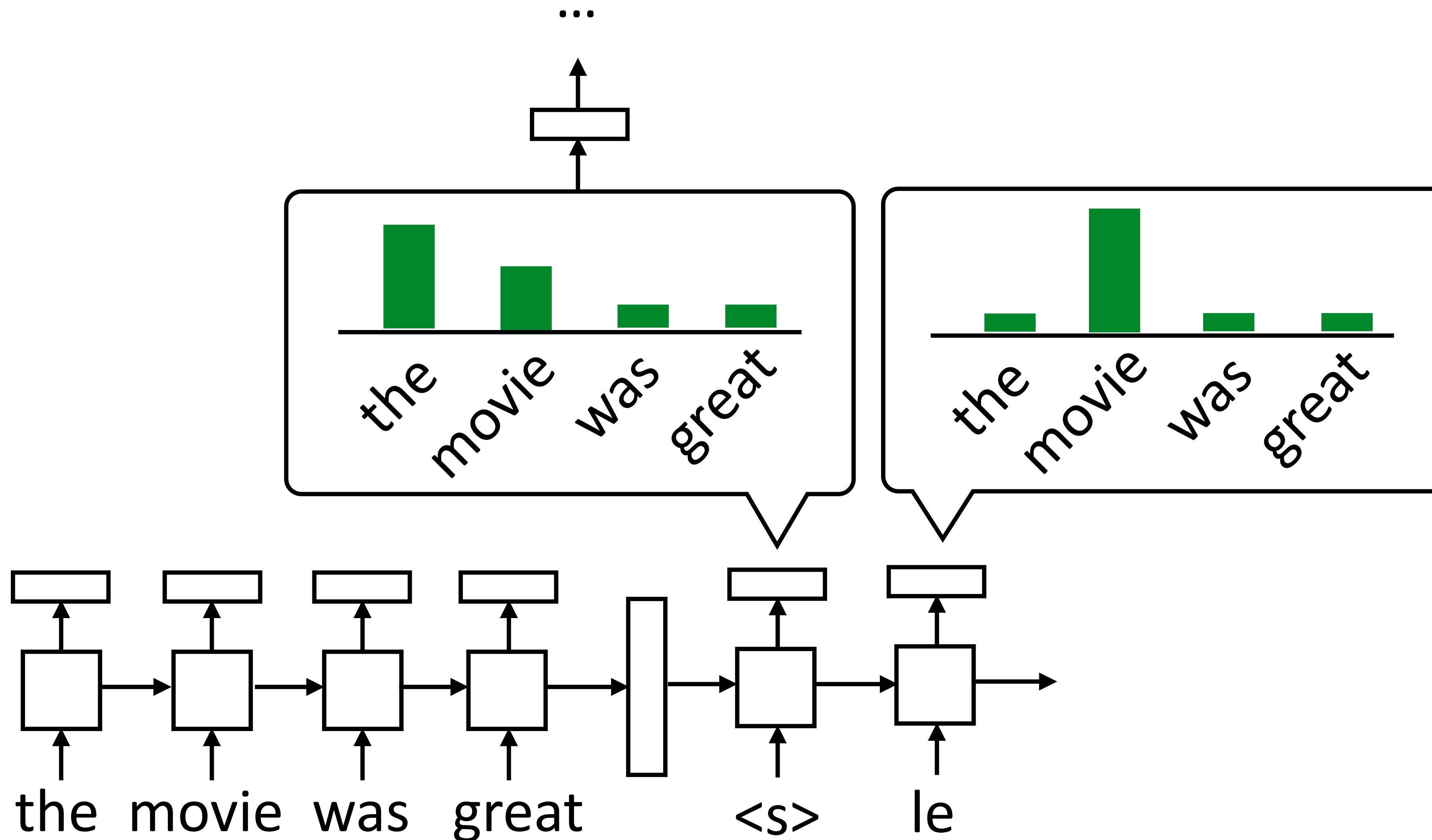
Attention



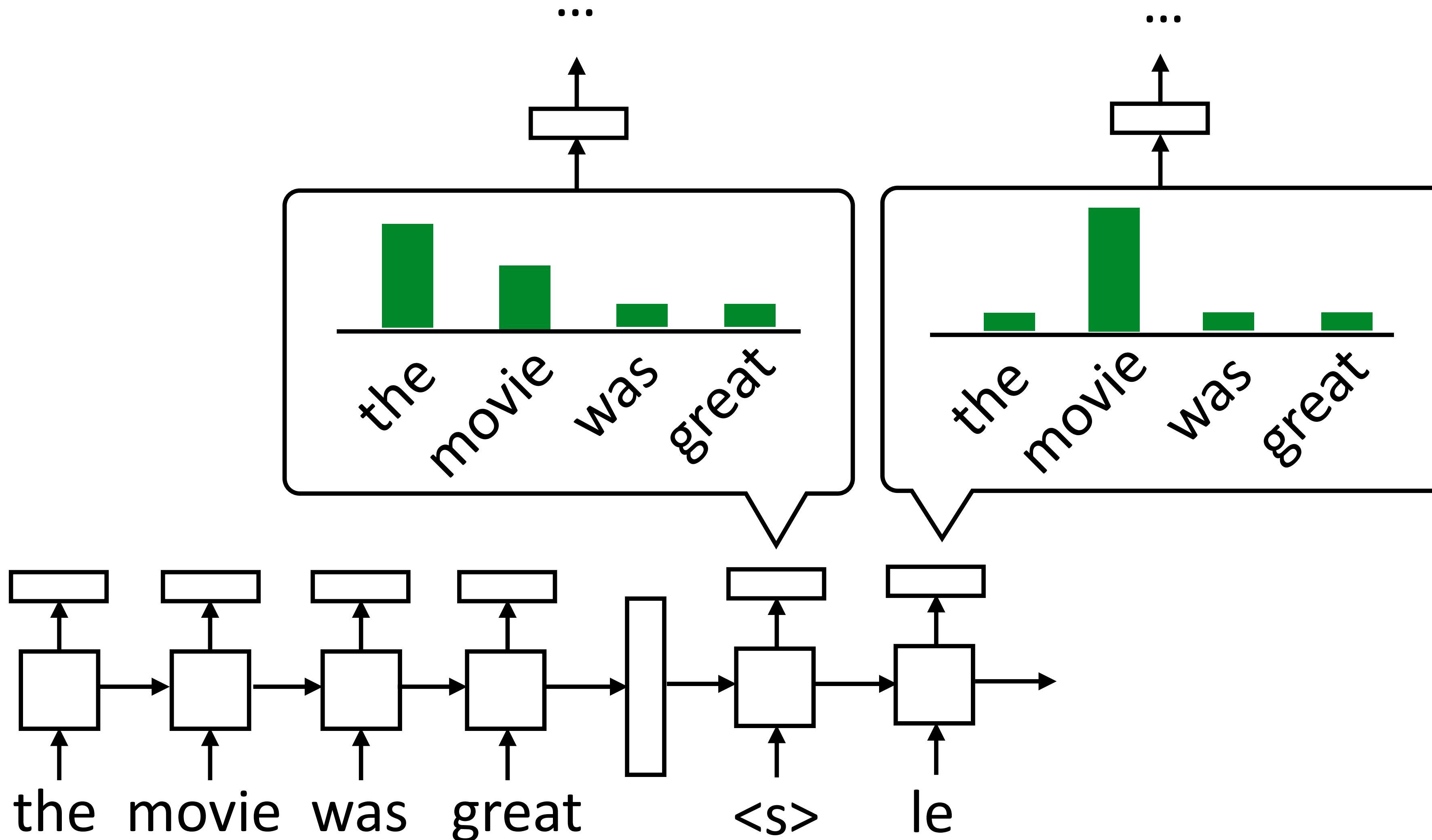
Attention



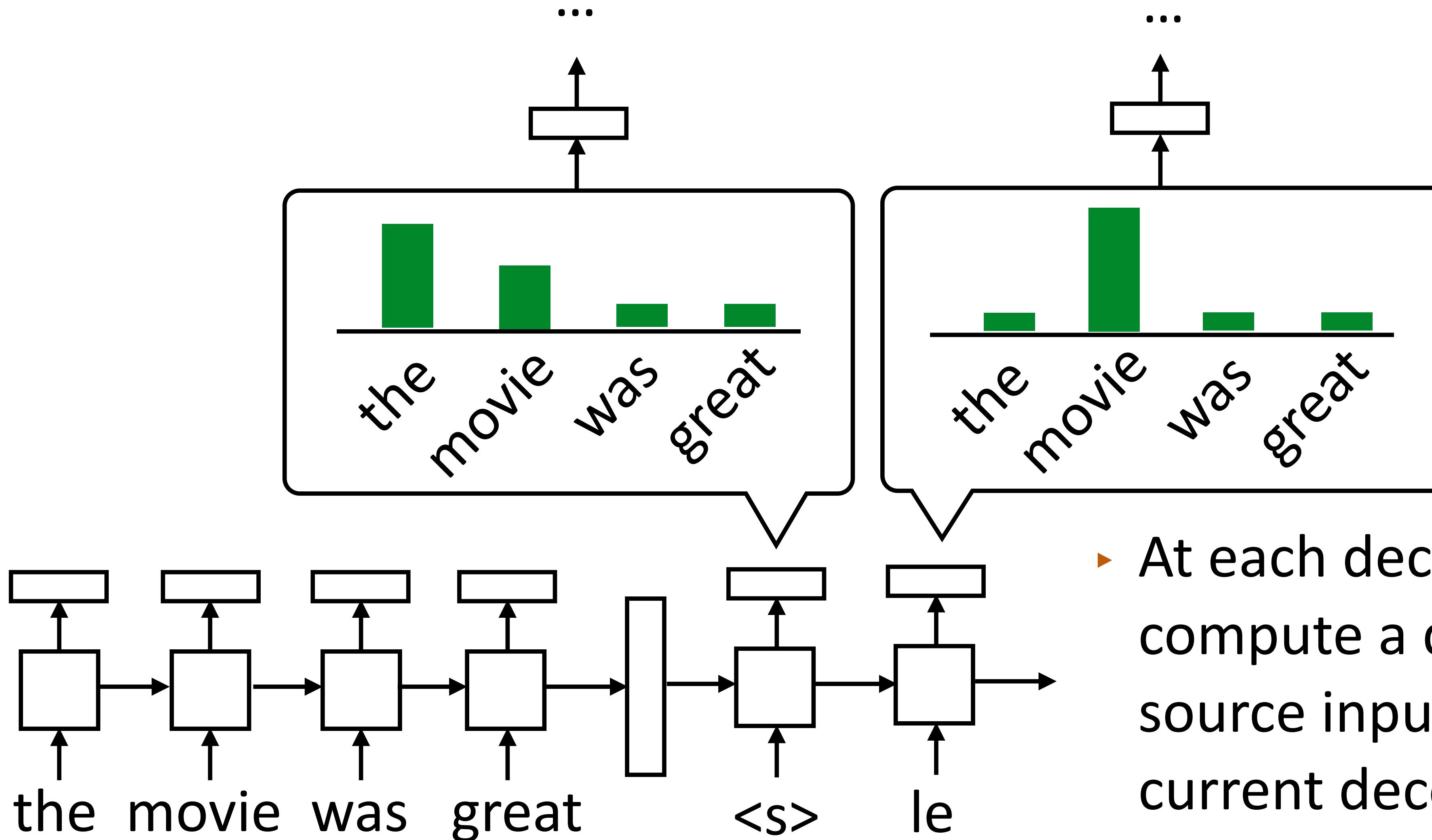
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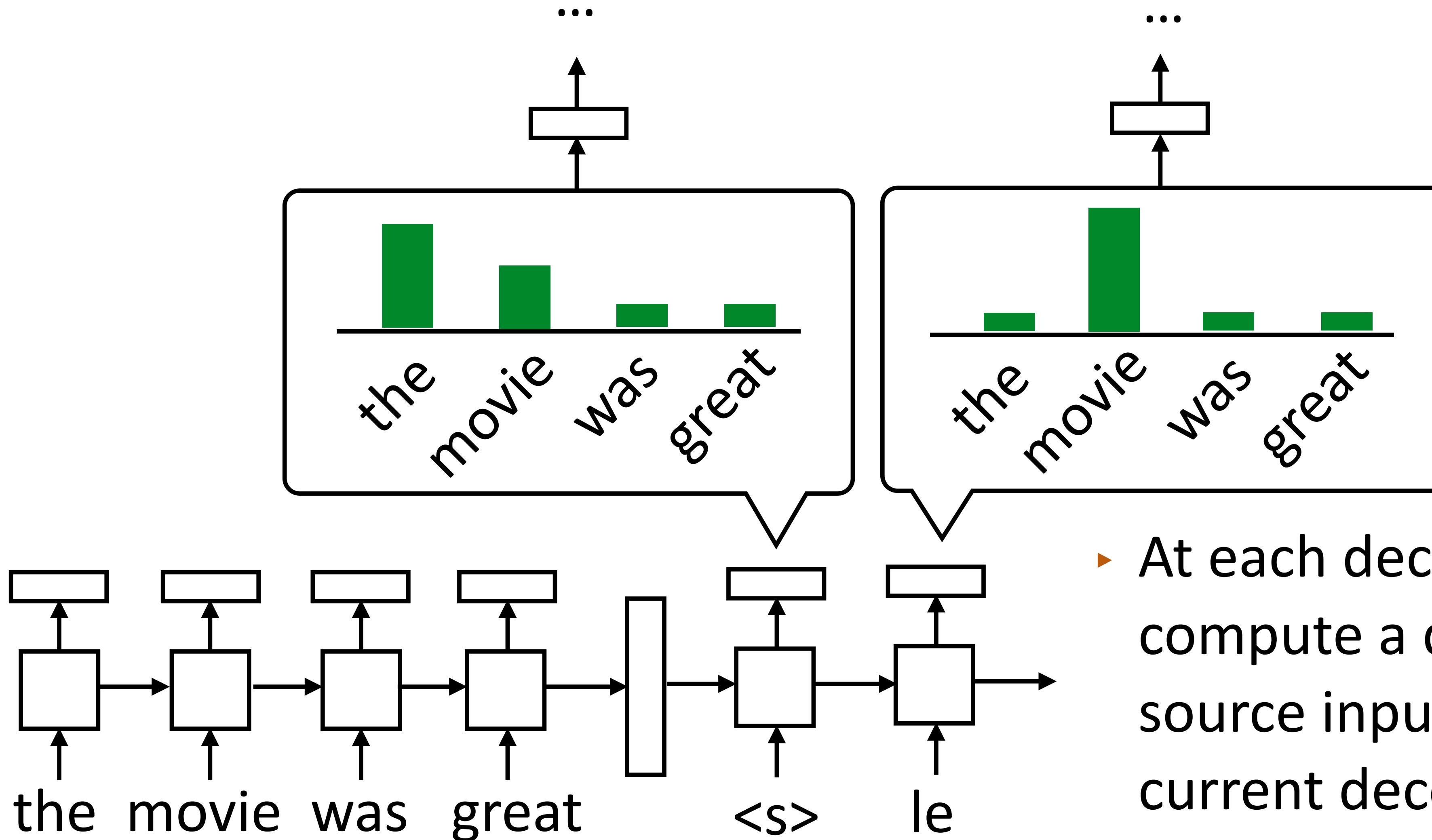
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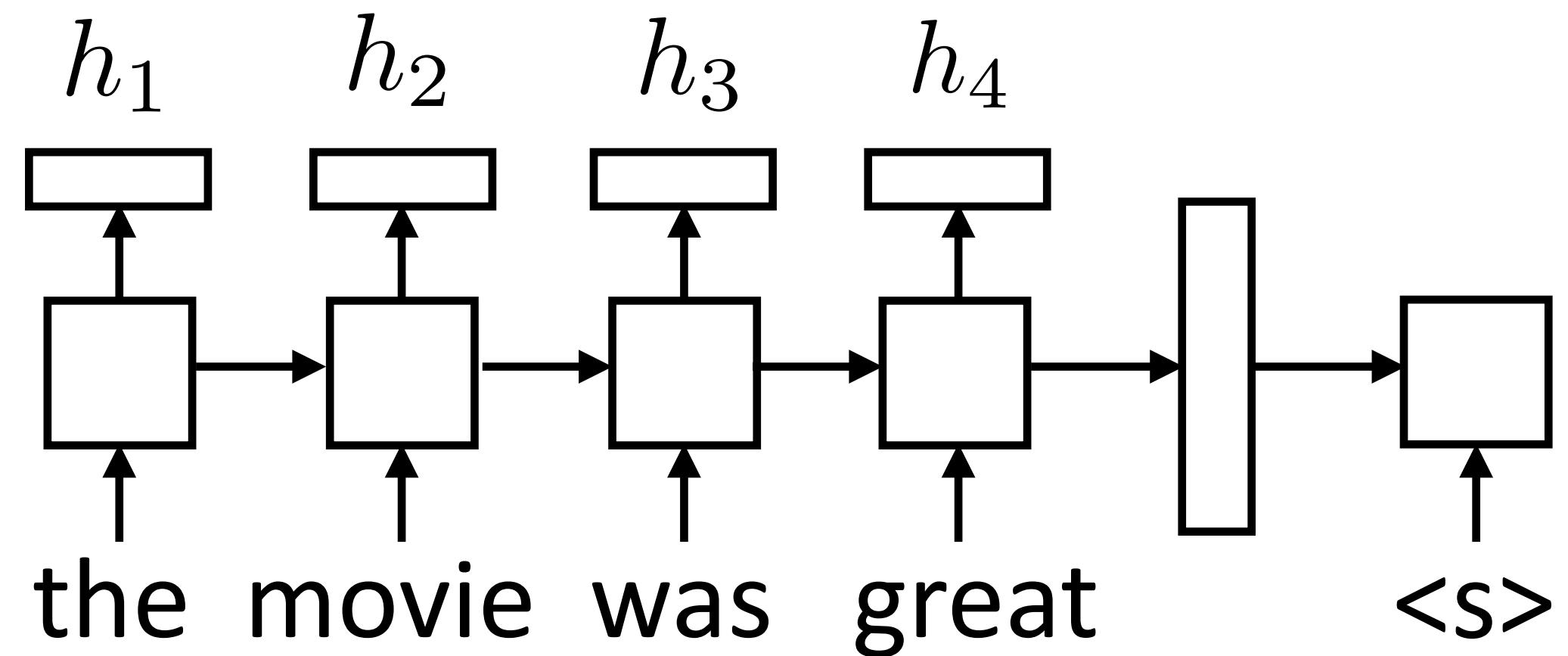
Attention



- ▶ At each decoder state, compute a distribution over source inputs based on current decoder state
- ▶ Use that in output layer

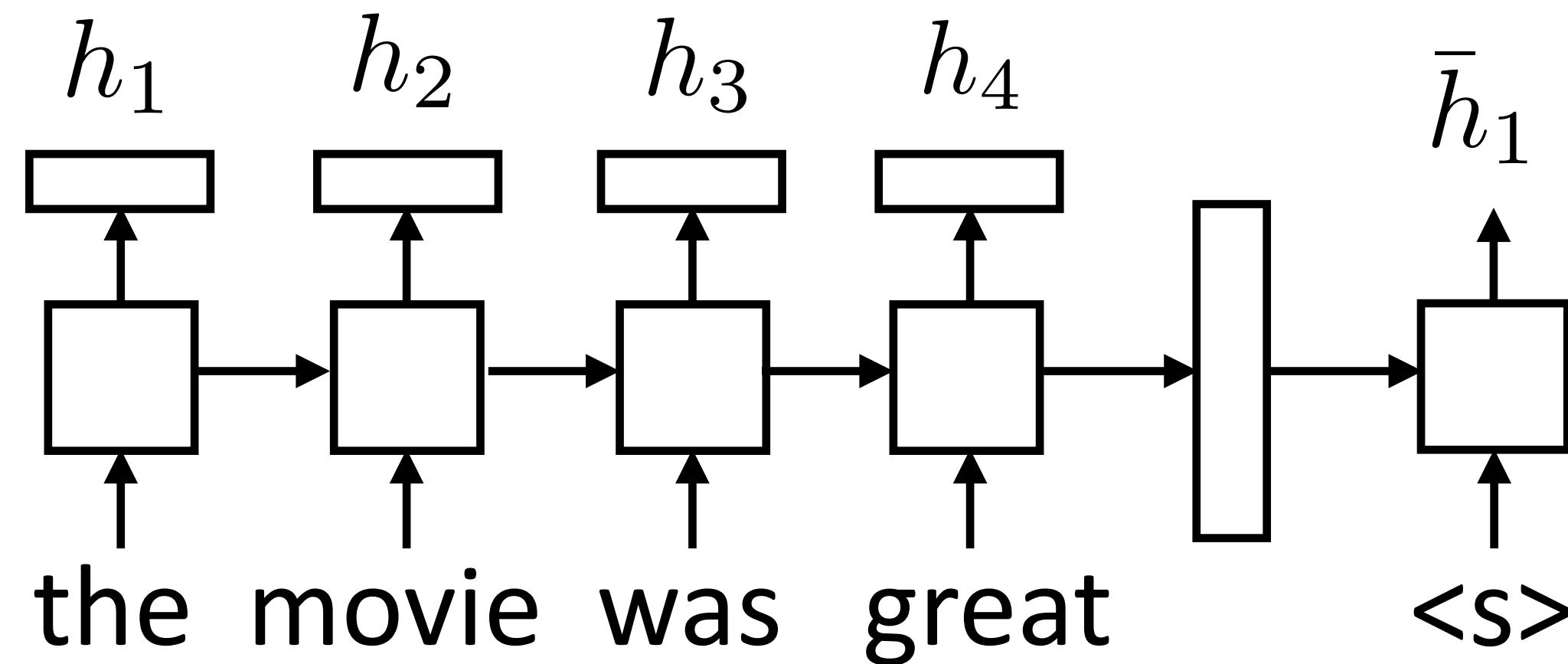
Attention

- ▶ For each decoder state,
compute weighted sum of
input states



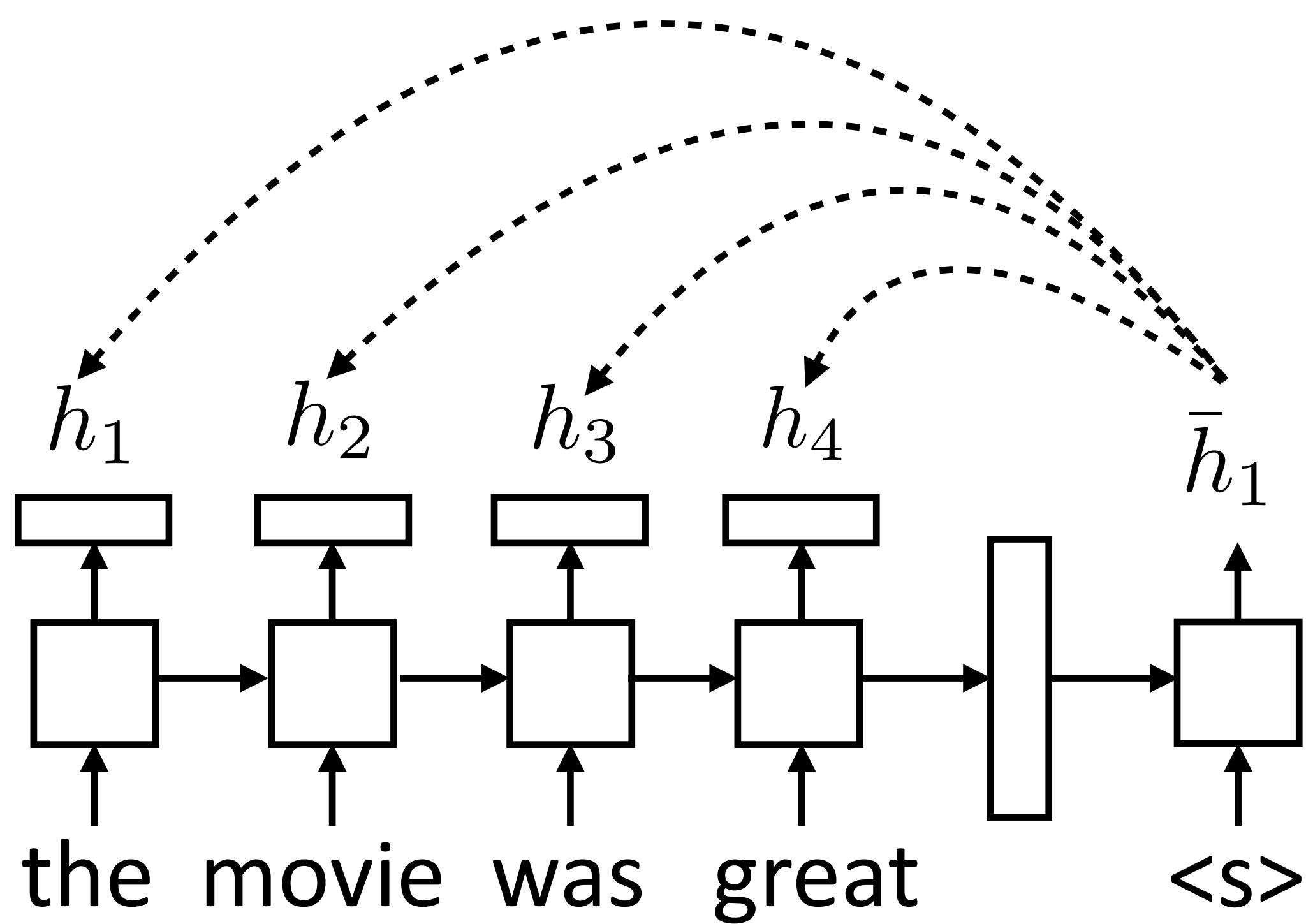
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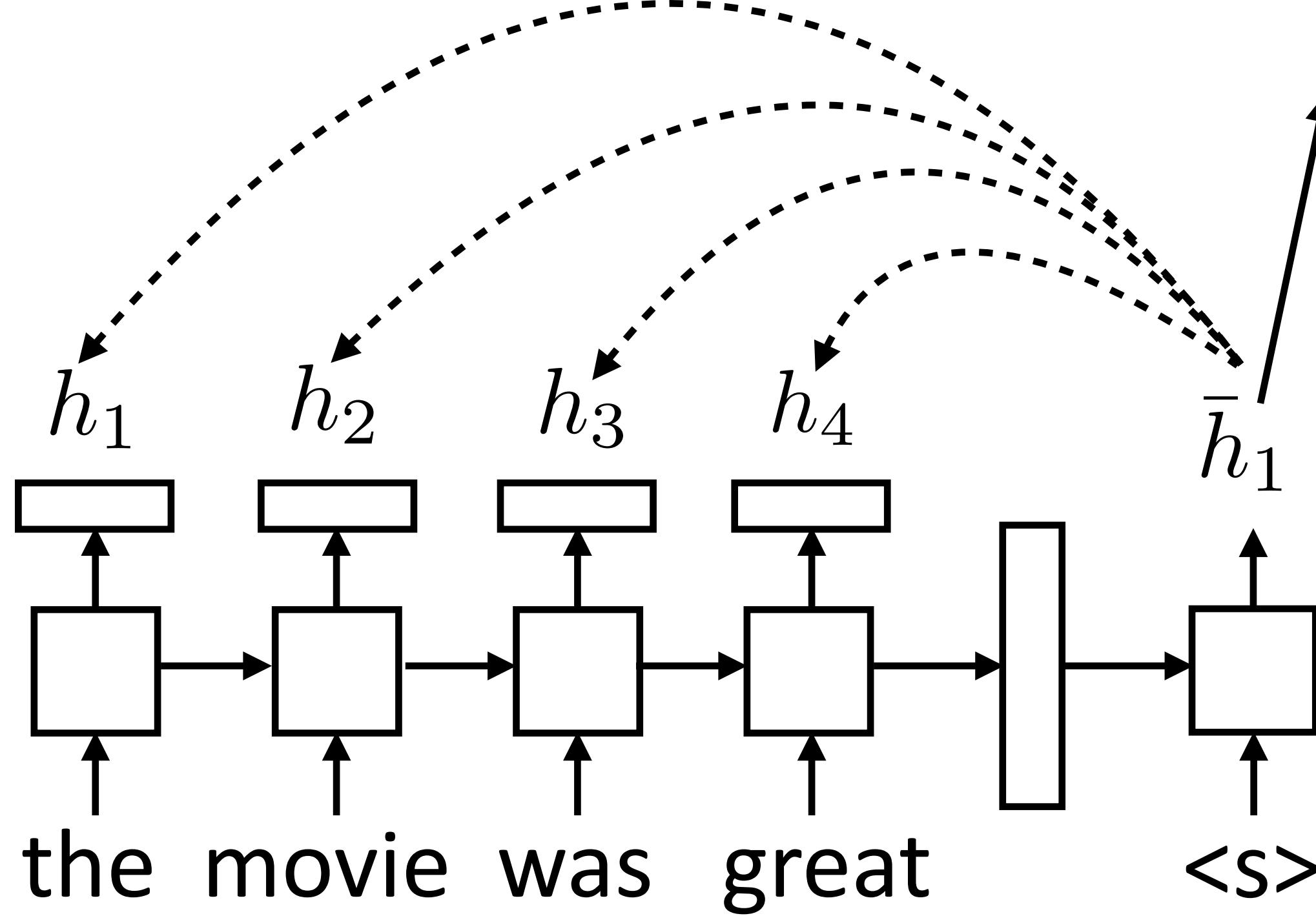
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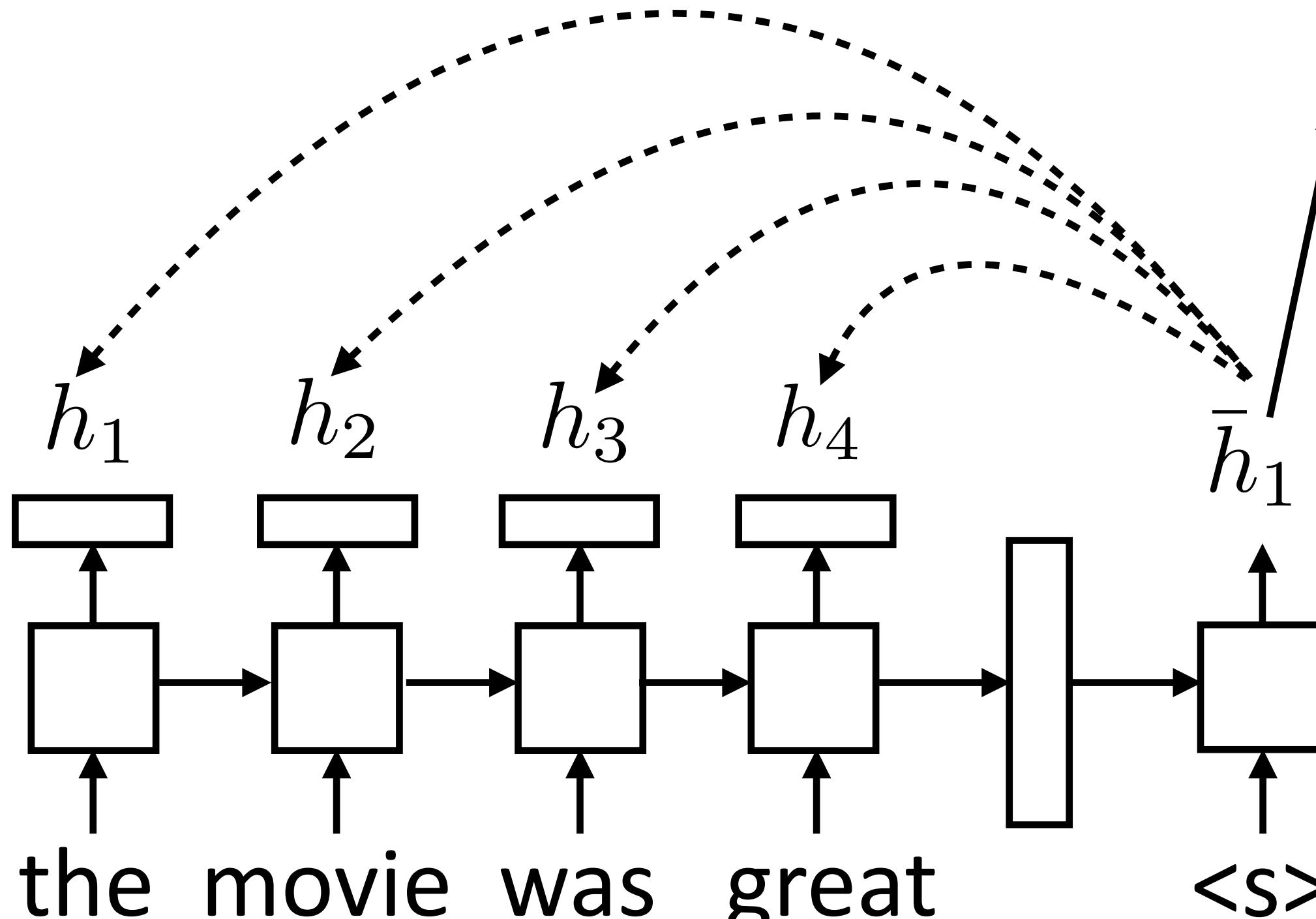
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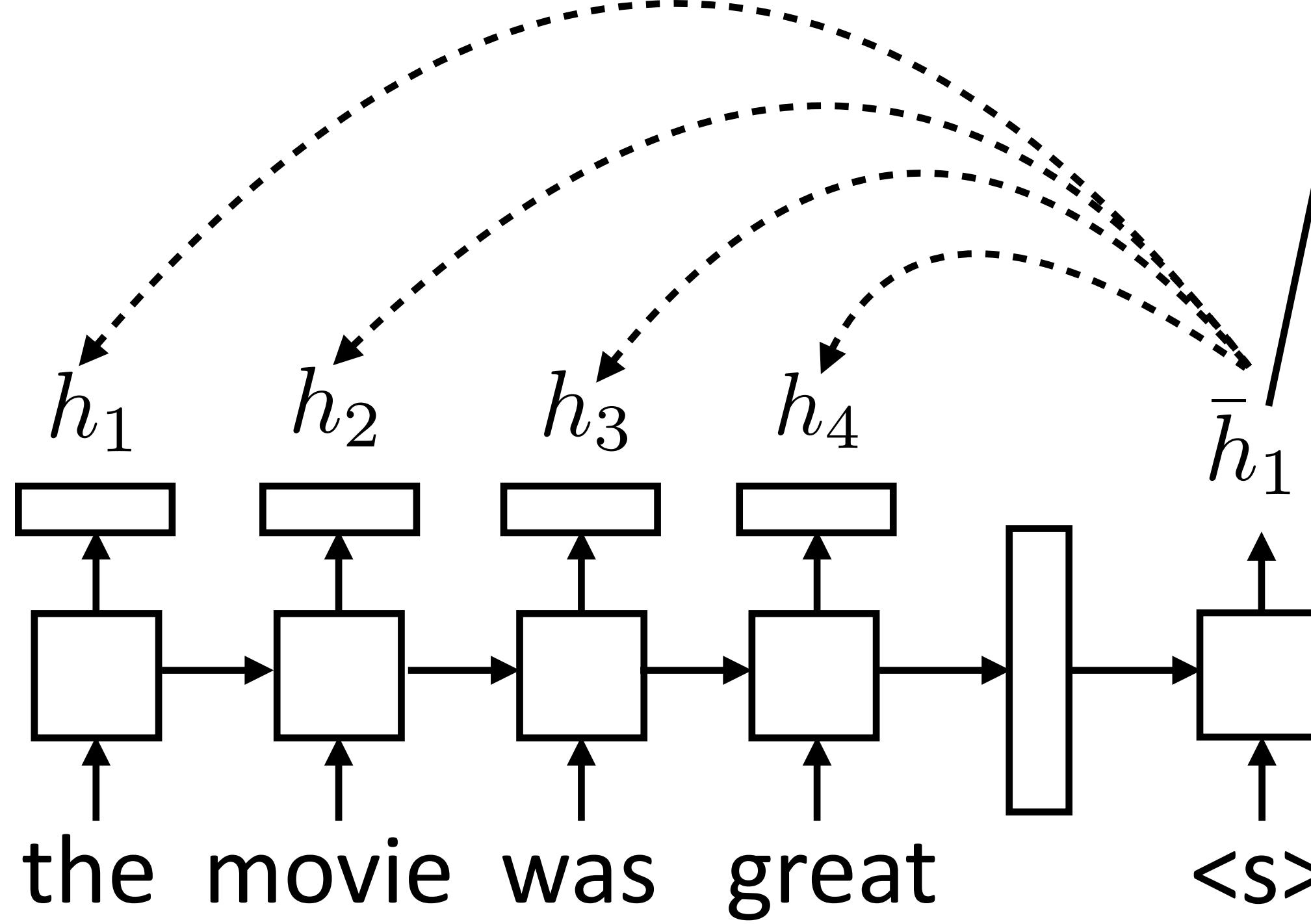


$$e_{ij} = f(\bar{h}_i, h_j)$$

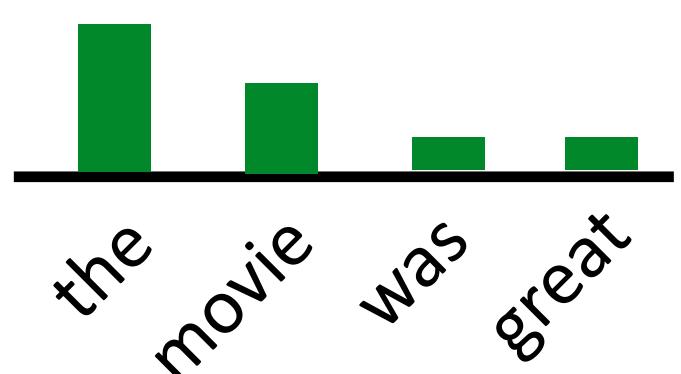
- ▶ Unnormalized scalar weight

Attention

- ▶ For each decoder state,
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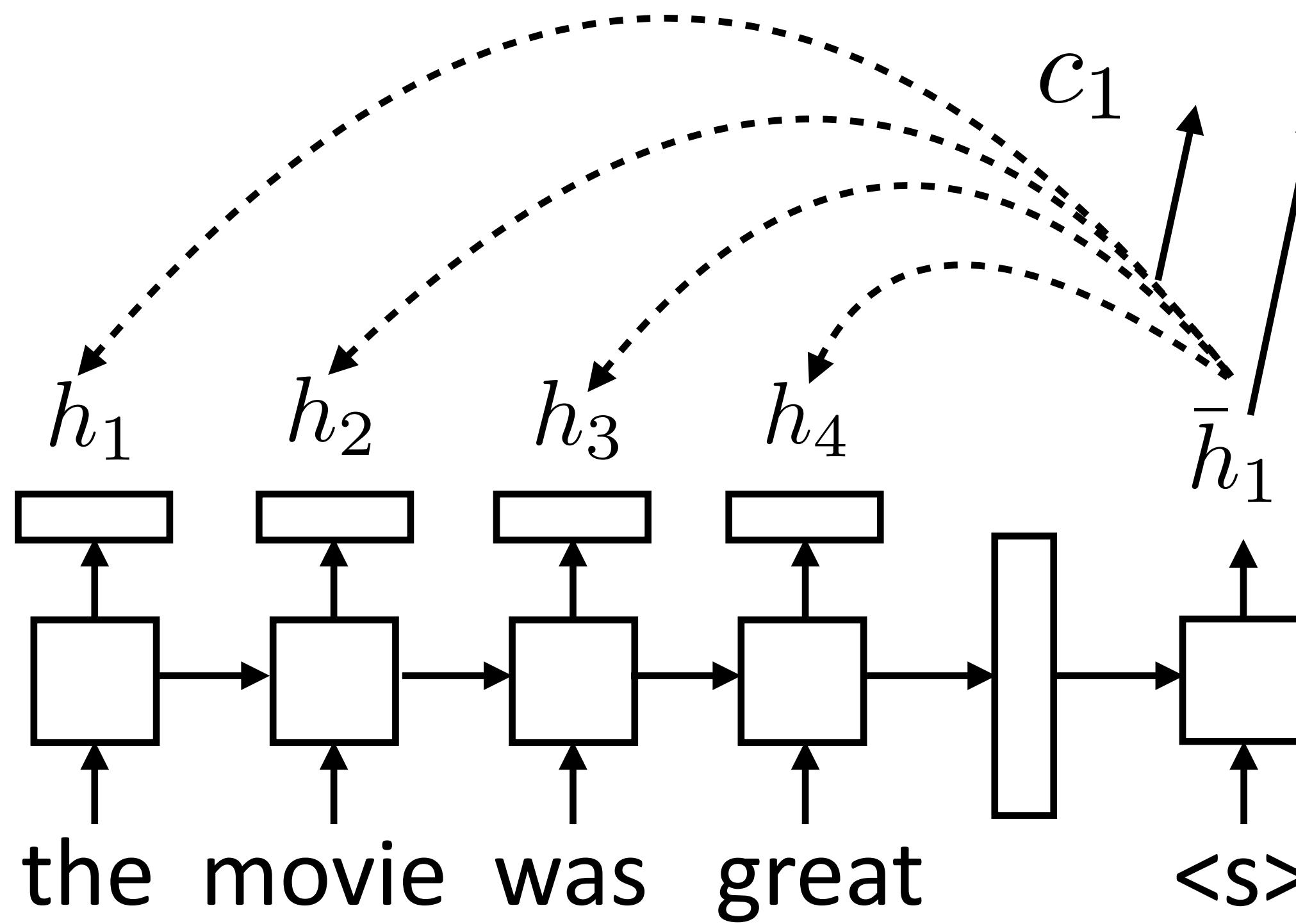
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$
$$e_{ij} = f(\bar{h}_i, h_j)$$



- ▶ Unnormalized scalar weight

Attention

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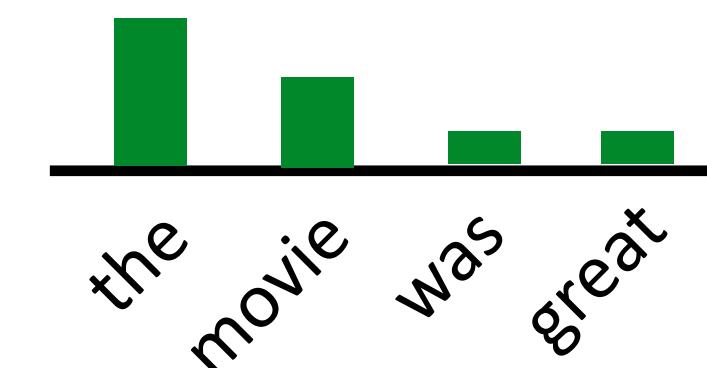


$$c_i = \sum_j \alpha_{ij} h_j$$

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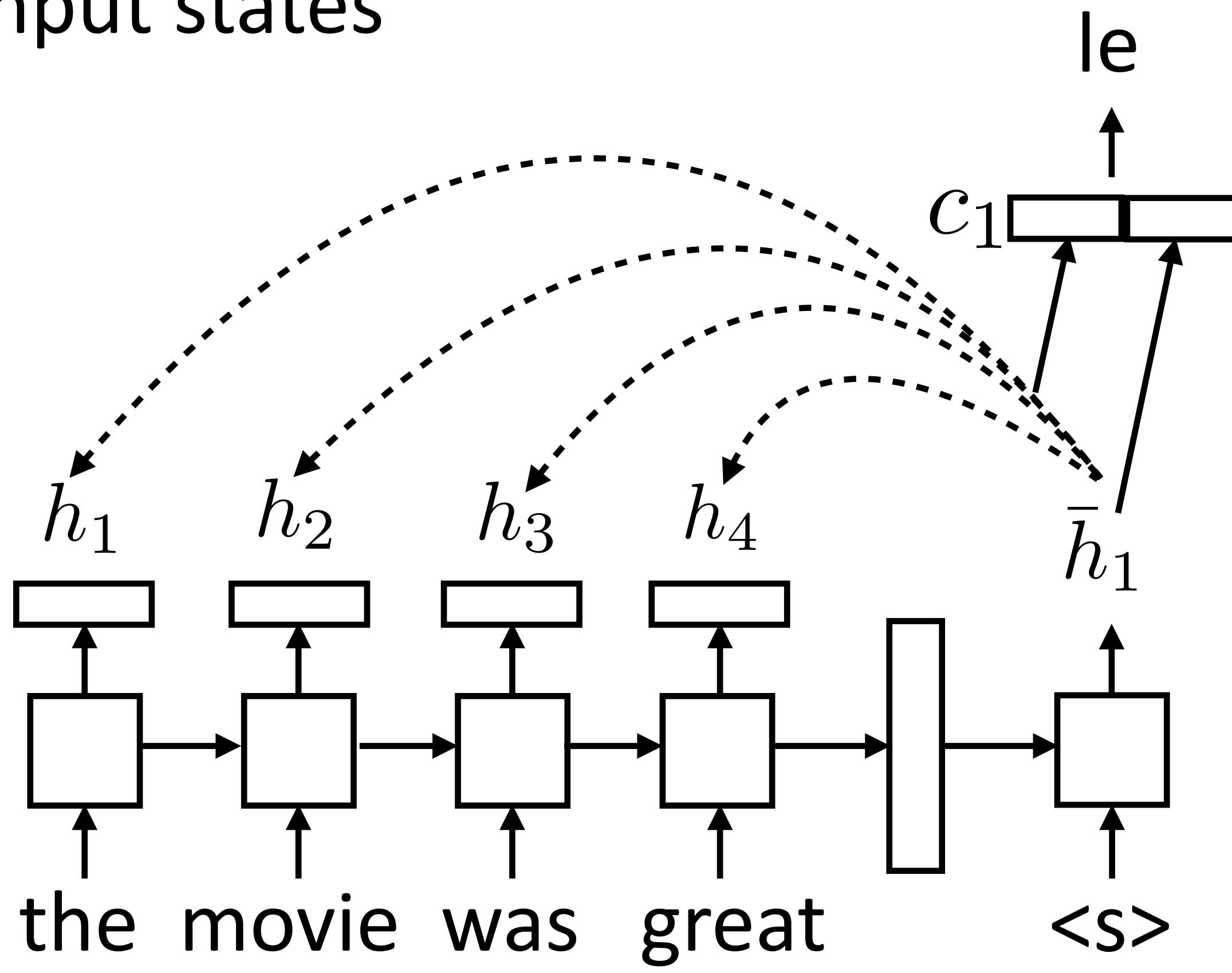
- ▶ Weighted sum
of input hidden
states (vector)



- ▶ Unnormalized
scalar weight

Attention

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compute weighted sum of
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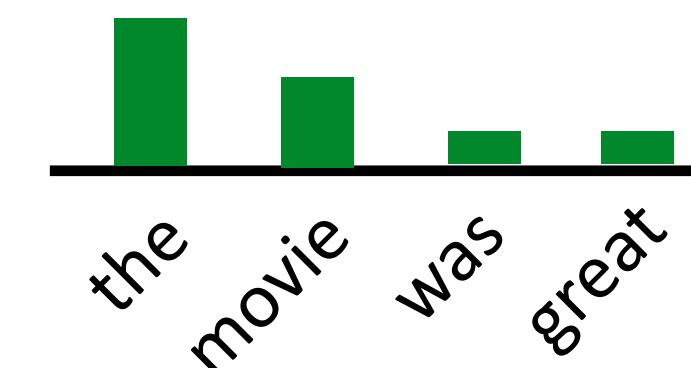


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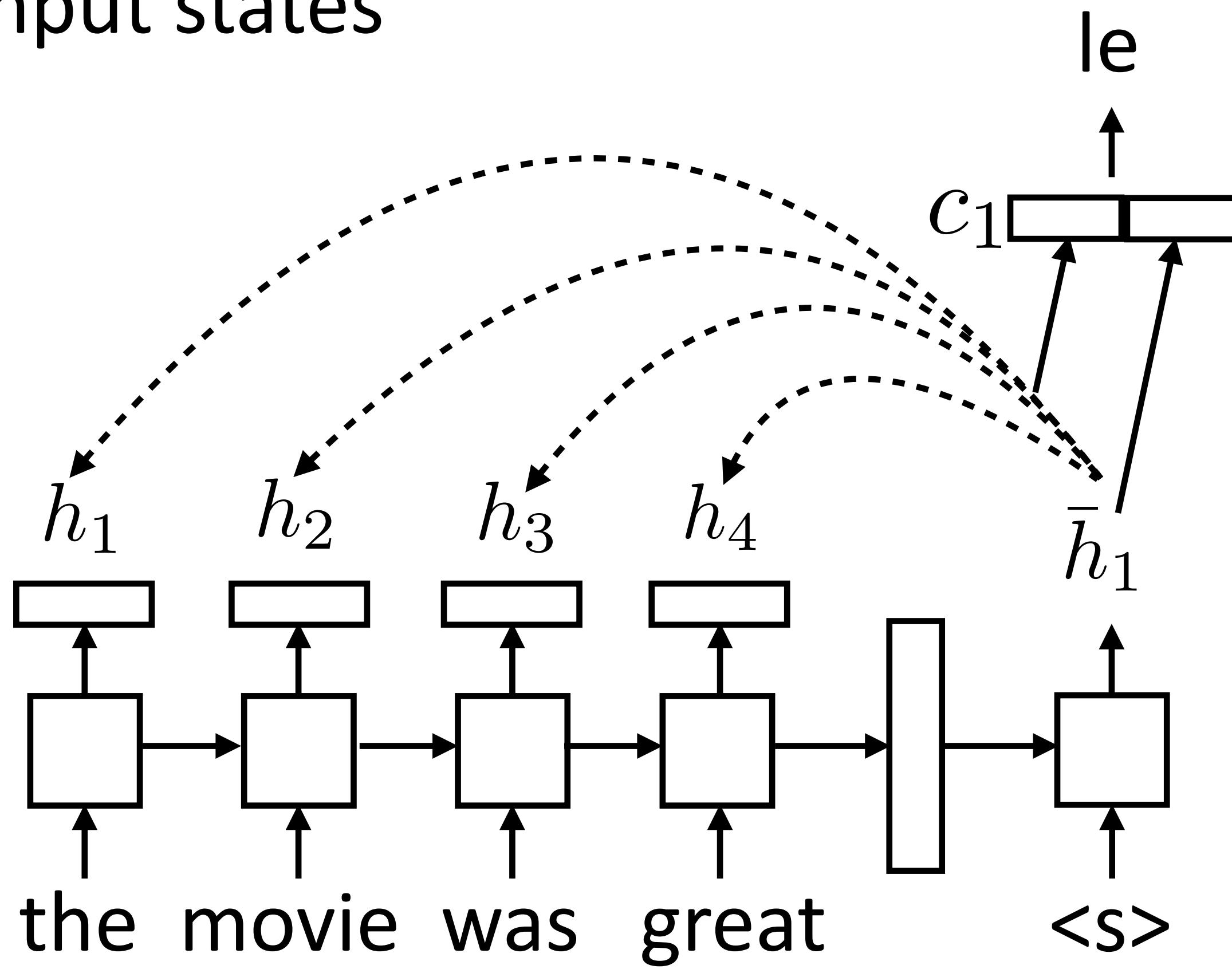
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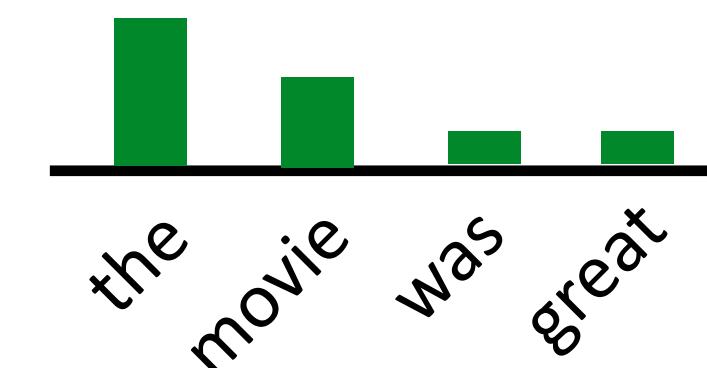
$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$

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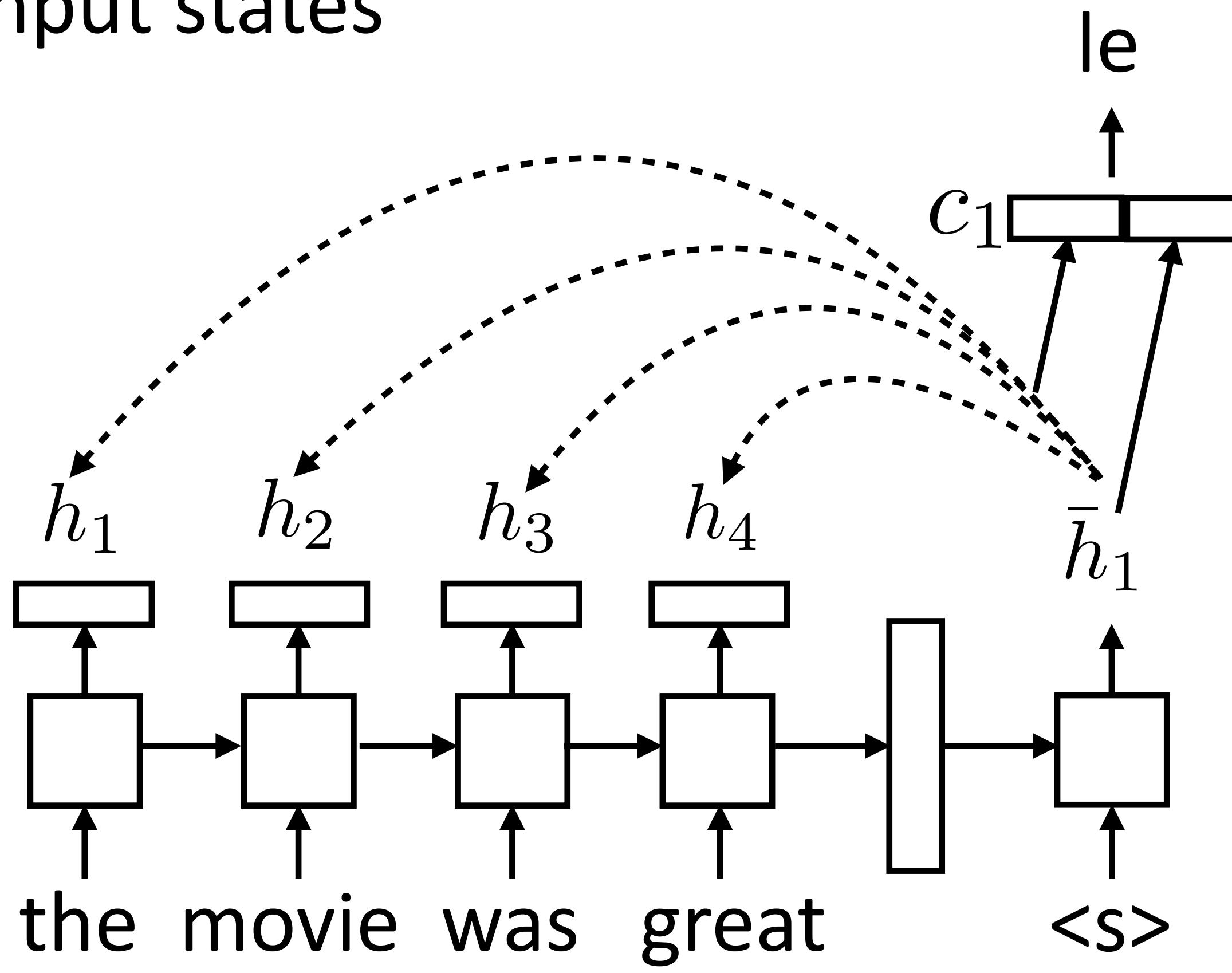
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Attention

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- ▶ No attn: $P(y_i|\mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W\bar{h}_i)$

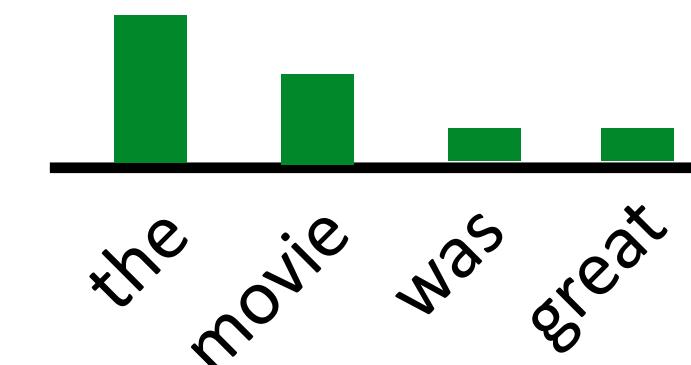
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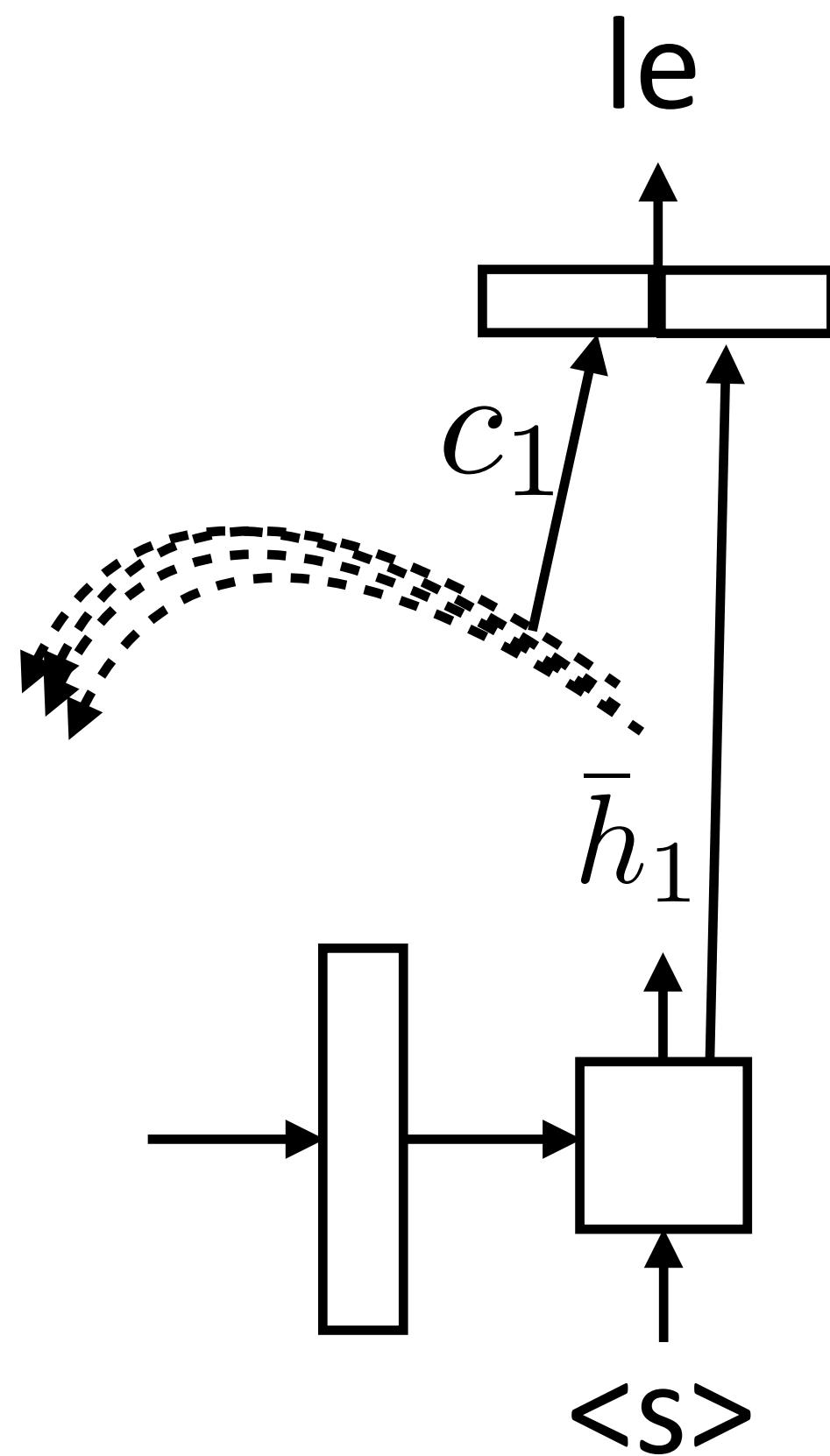
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Attention

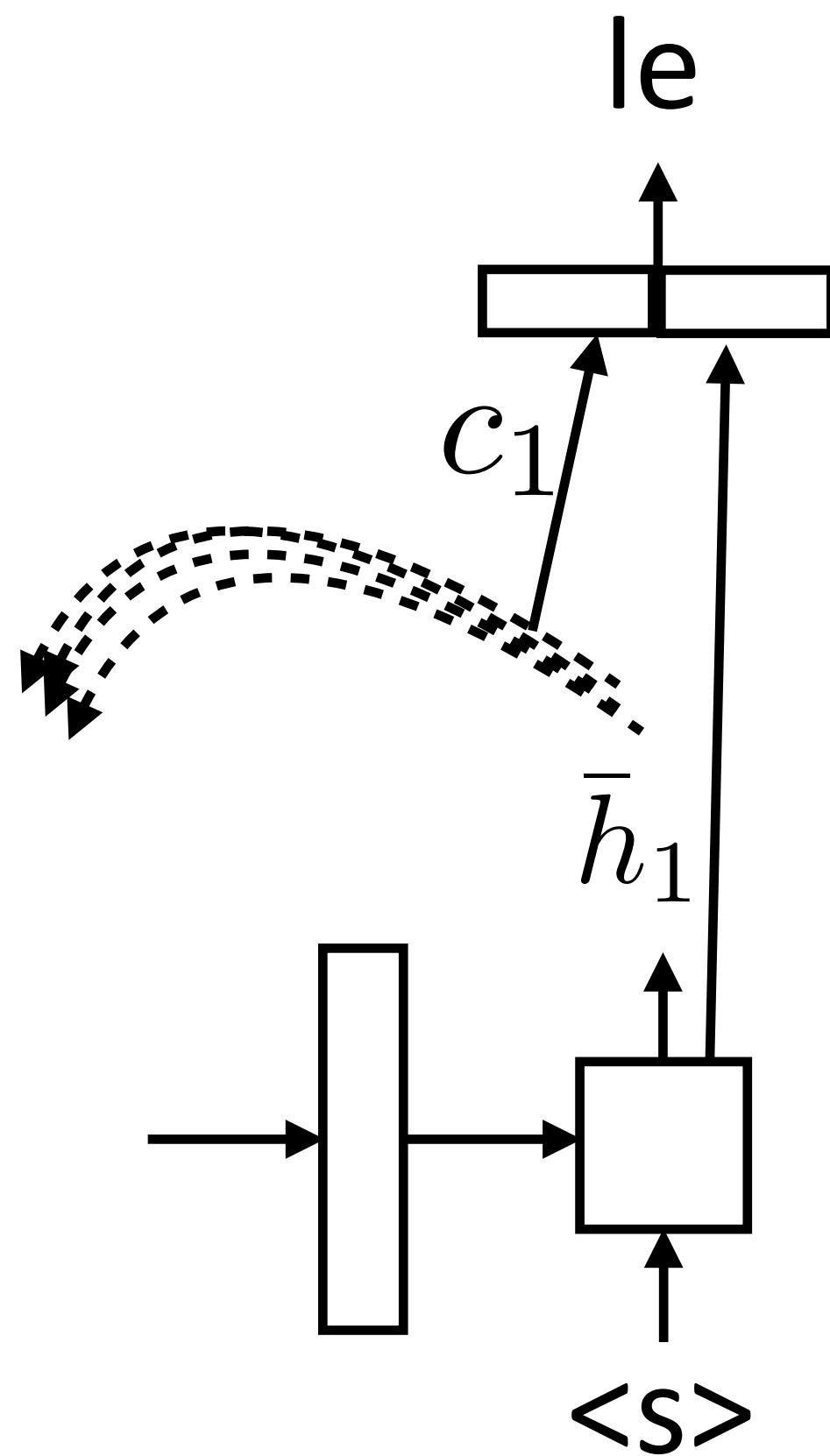


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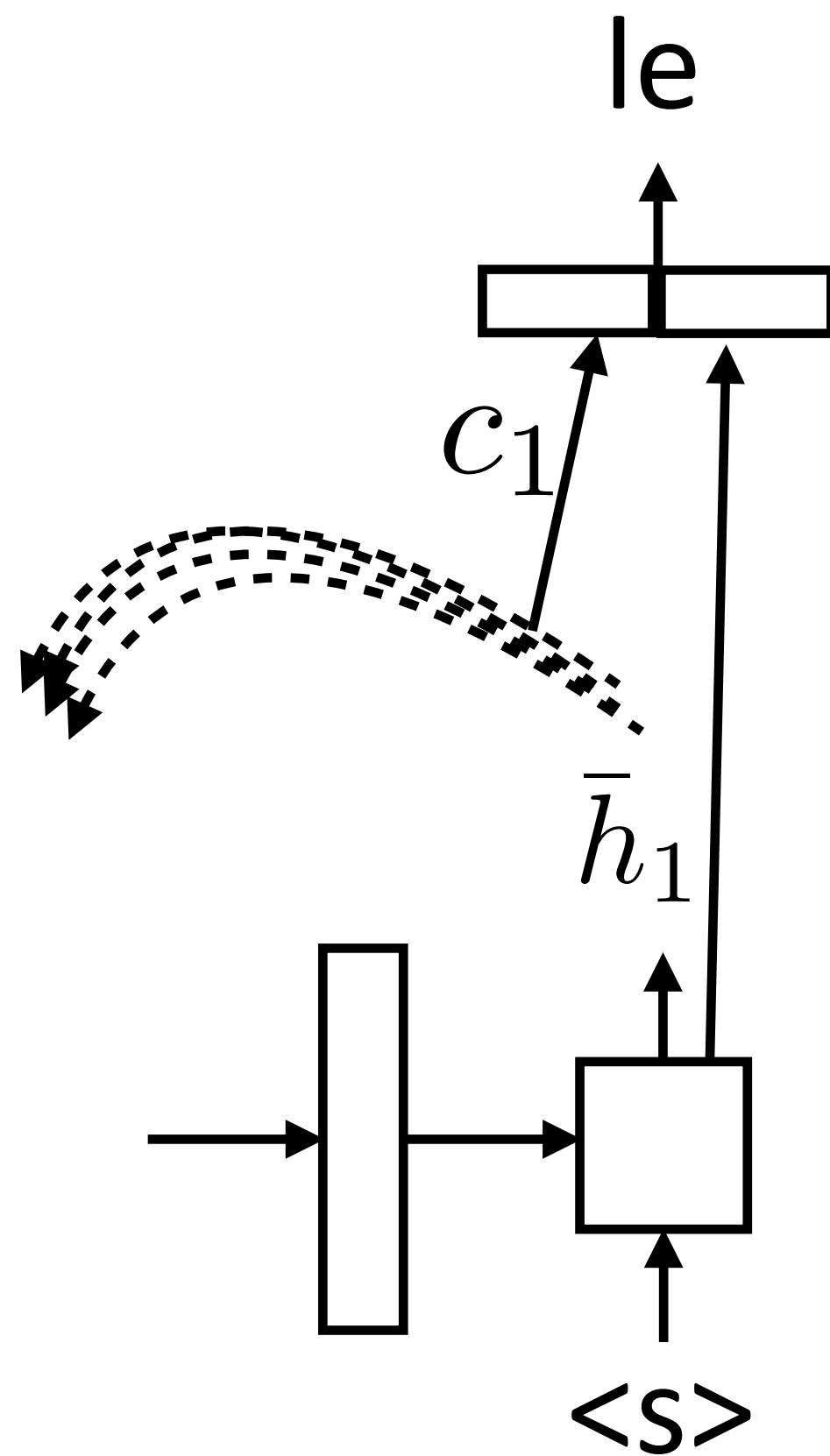
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► Bahdanau+ (2014): additive

Attention



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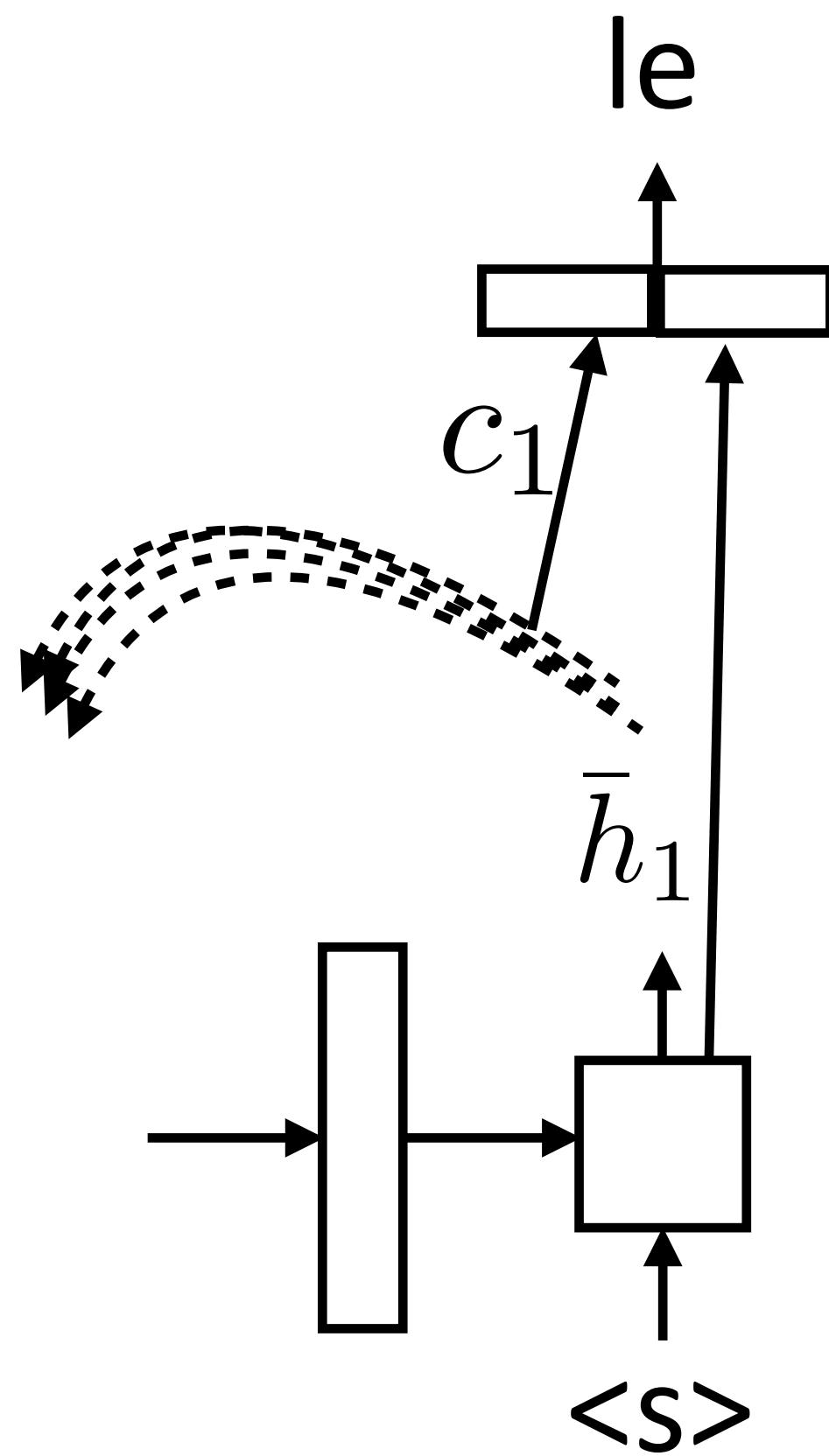
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$$f(\bar{h}_i, h_j) = \bar{h}_i \cdot h_j$$

► Luong+ (2015): dot product

Attention



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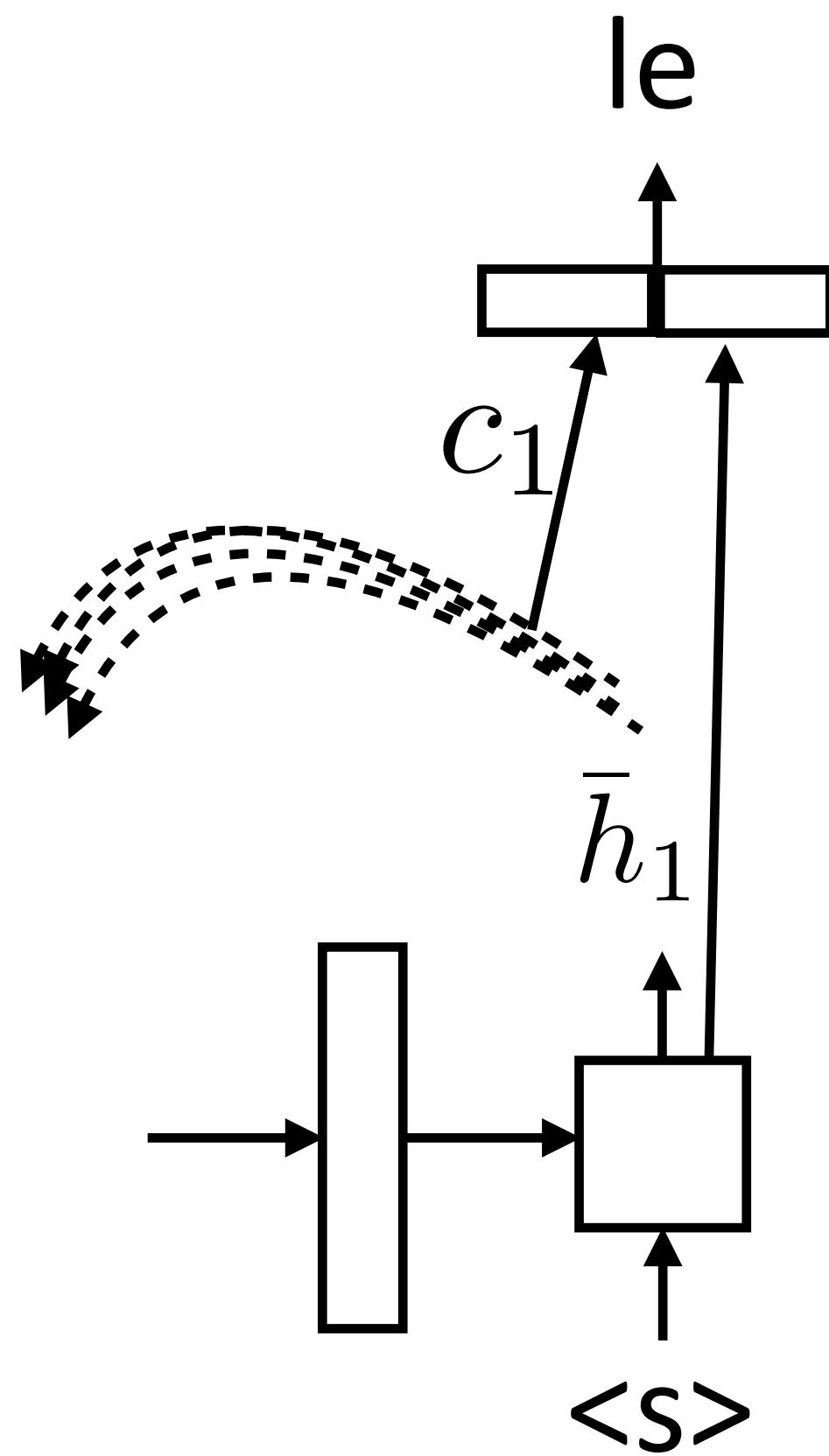
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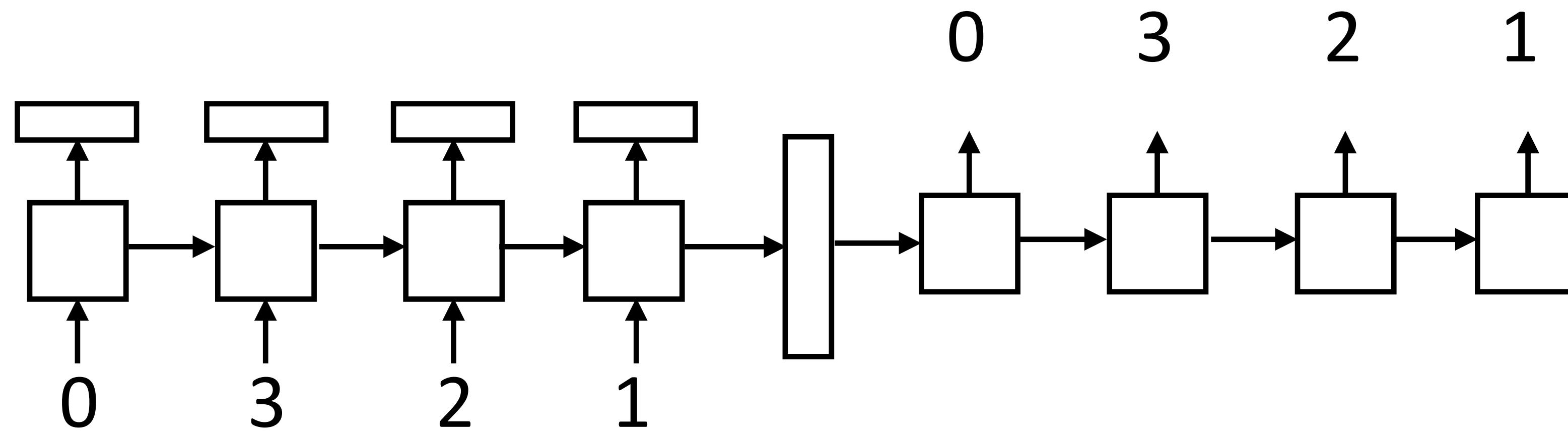
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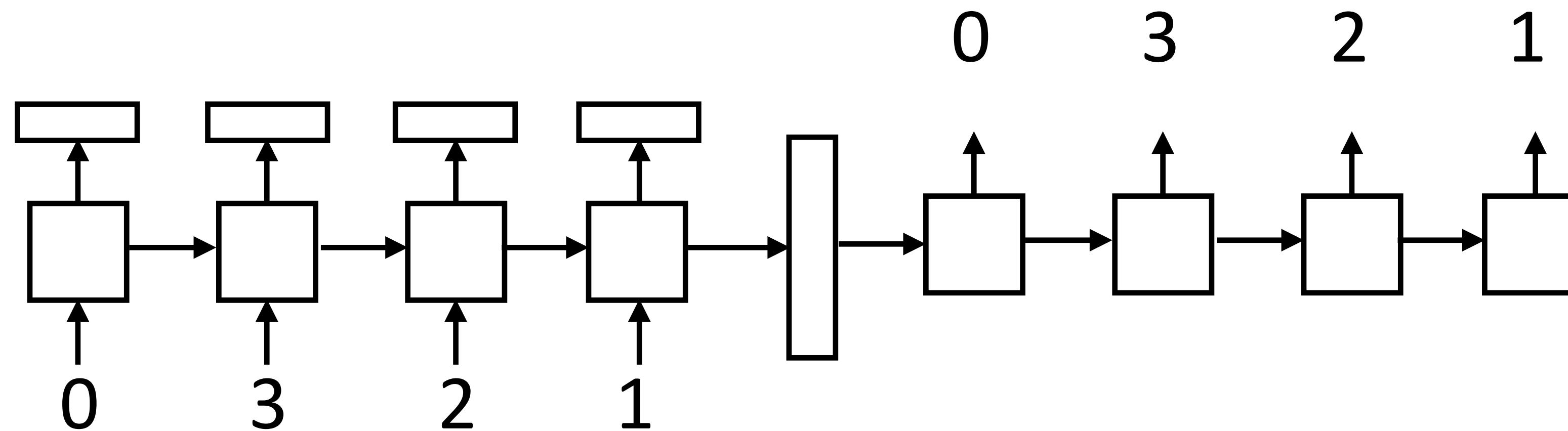
- Note that this all uses outputs of hidden layers

What can attention do?



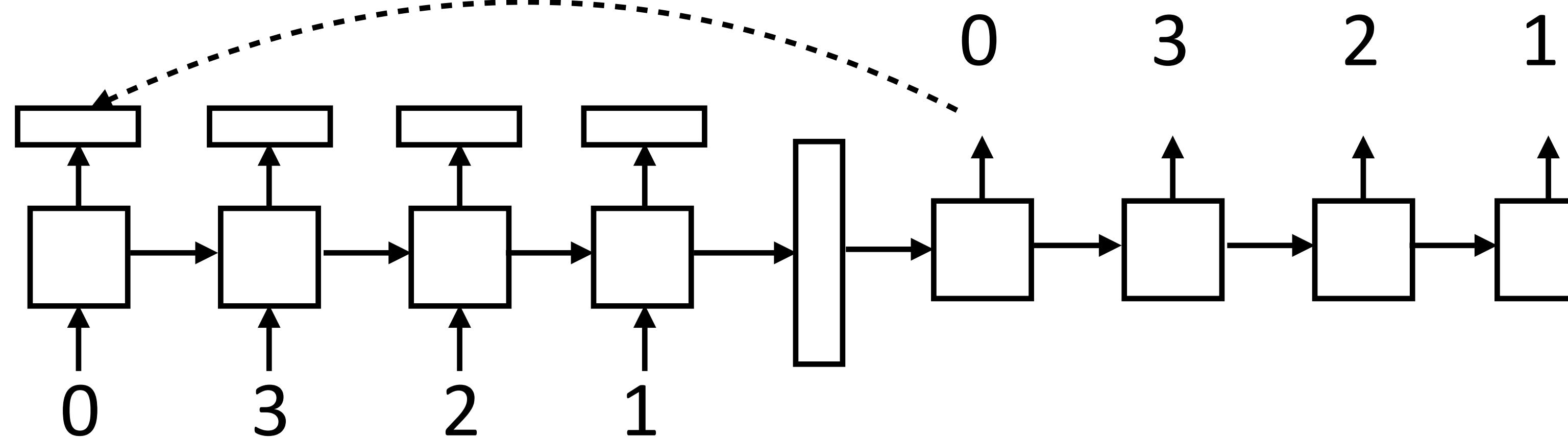
What can attention do?

- ▶ Learning to copy – how might this work?



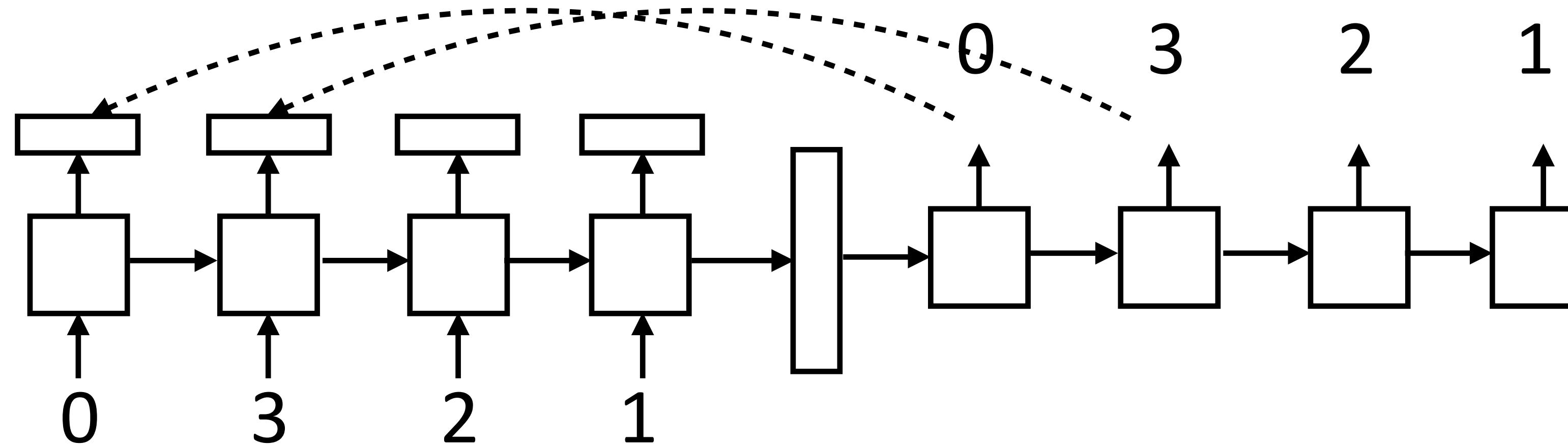
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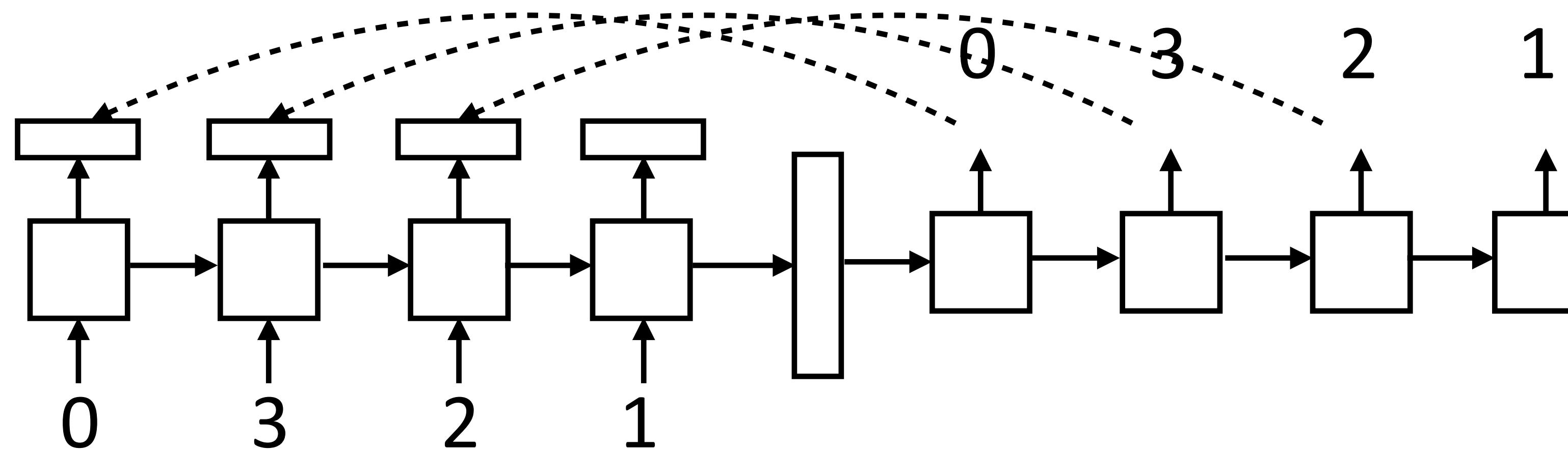
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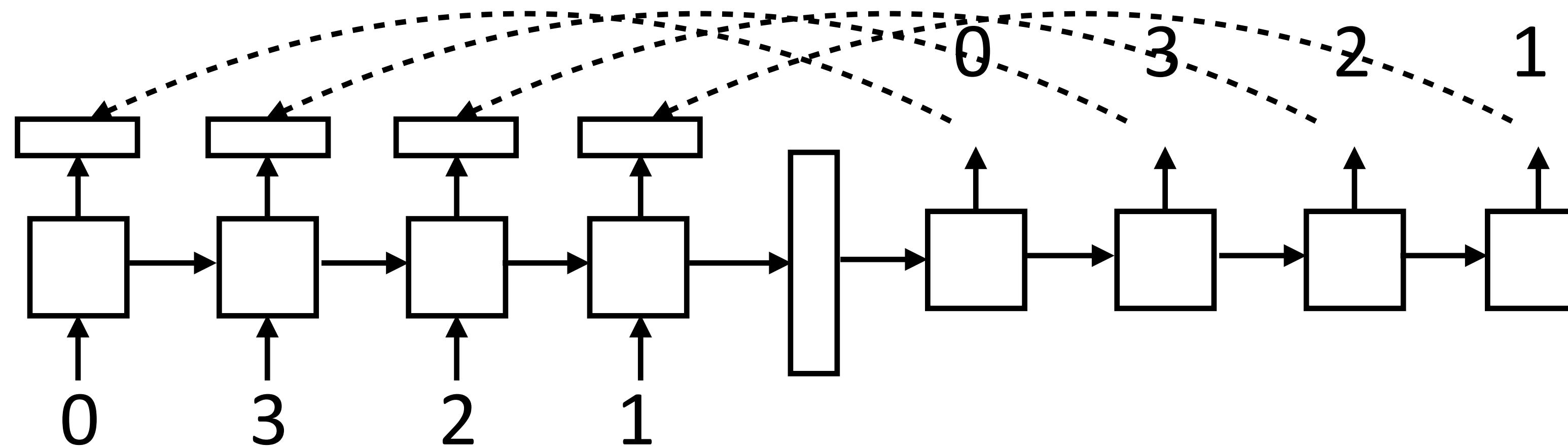
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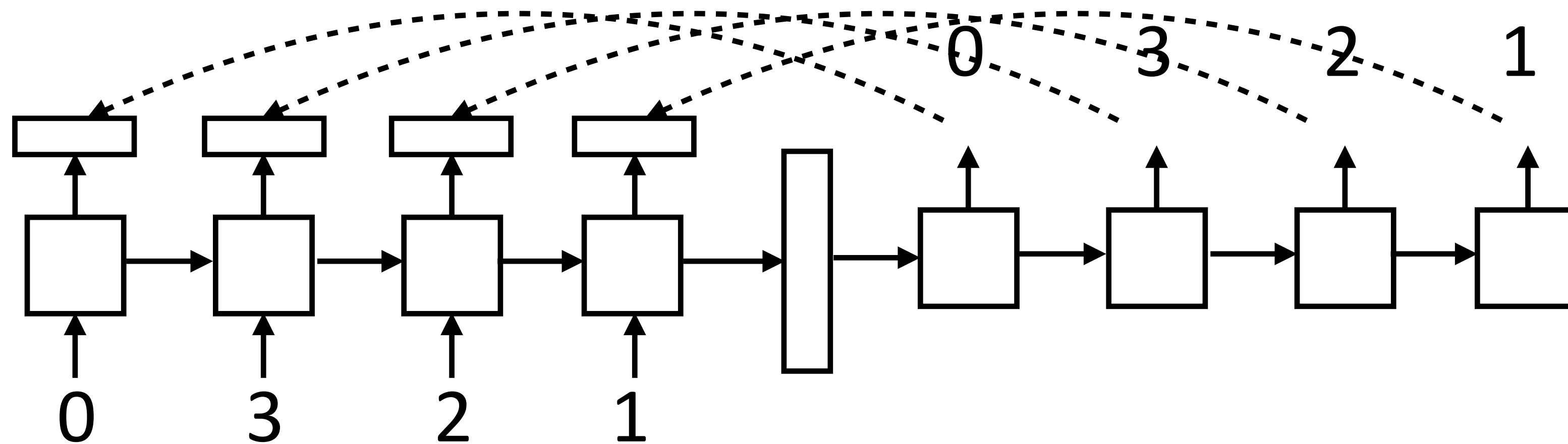
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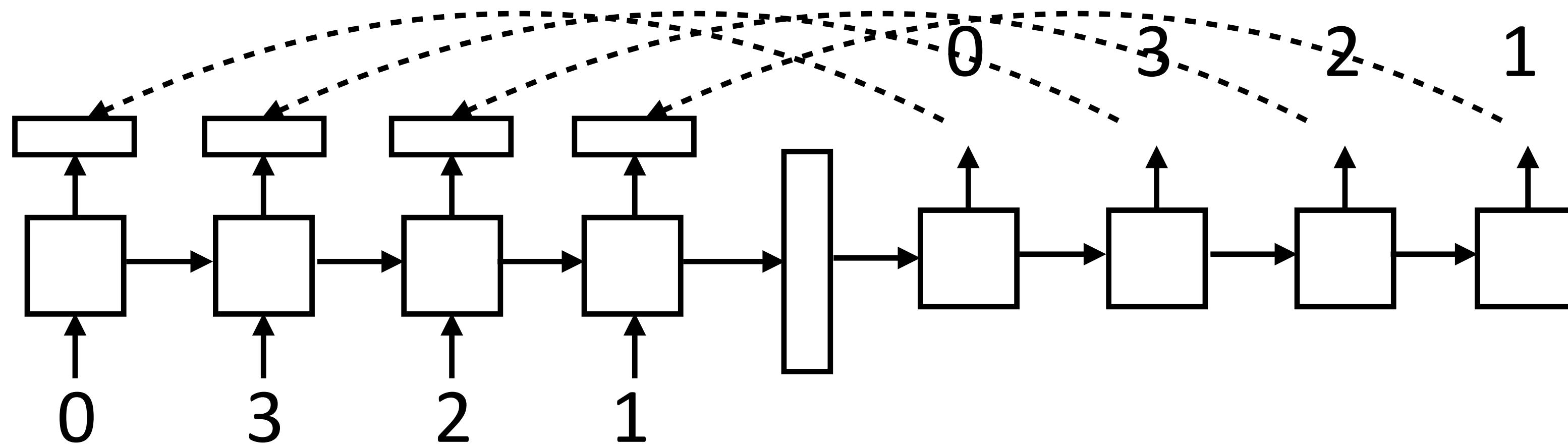
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- ▶ LSTM can learn to count with the right weight matrix

What can attention do?

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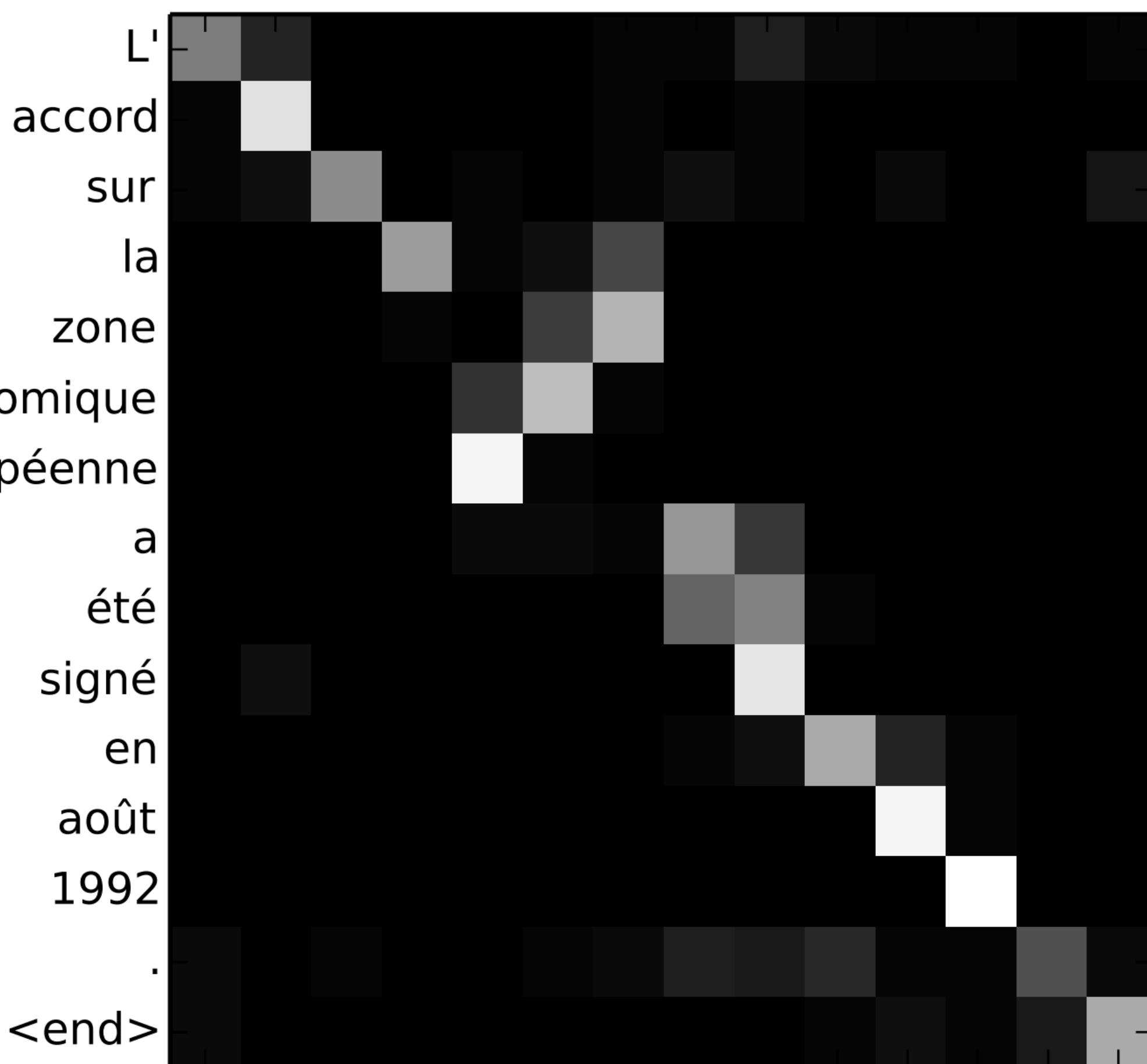


- ▶ LSTM can learn to count with the right weight matrix
- ▶ This is effectively position-based addressing

Attention

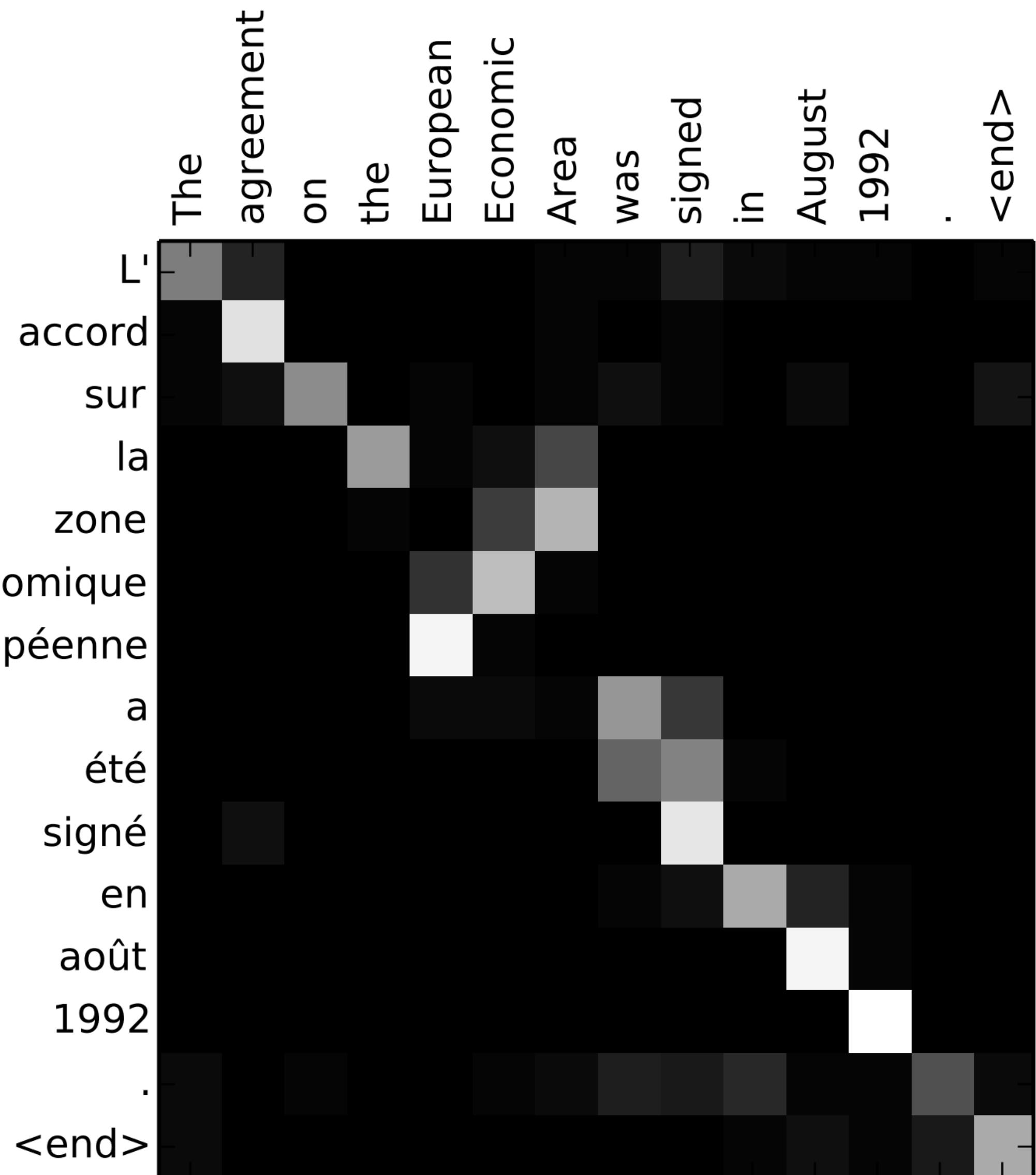
The agreement on the European Economic Area was signed in August 1992 . <end>

L'accord sur la zone économique européenne a été signé en août 1992 . <end>



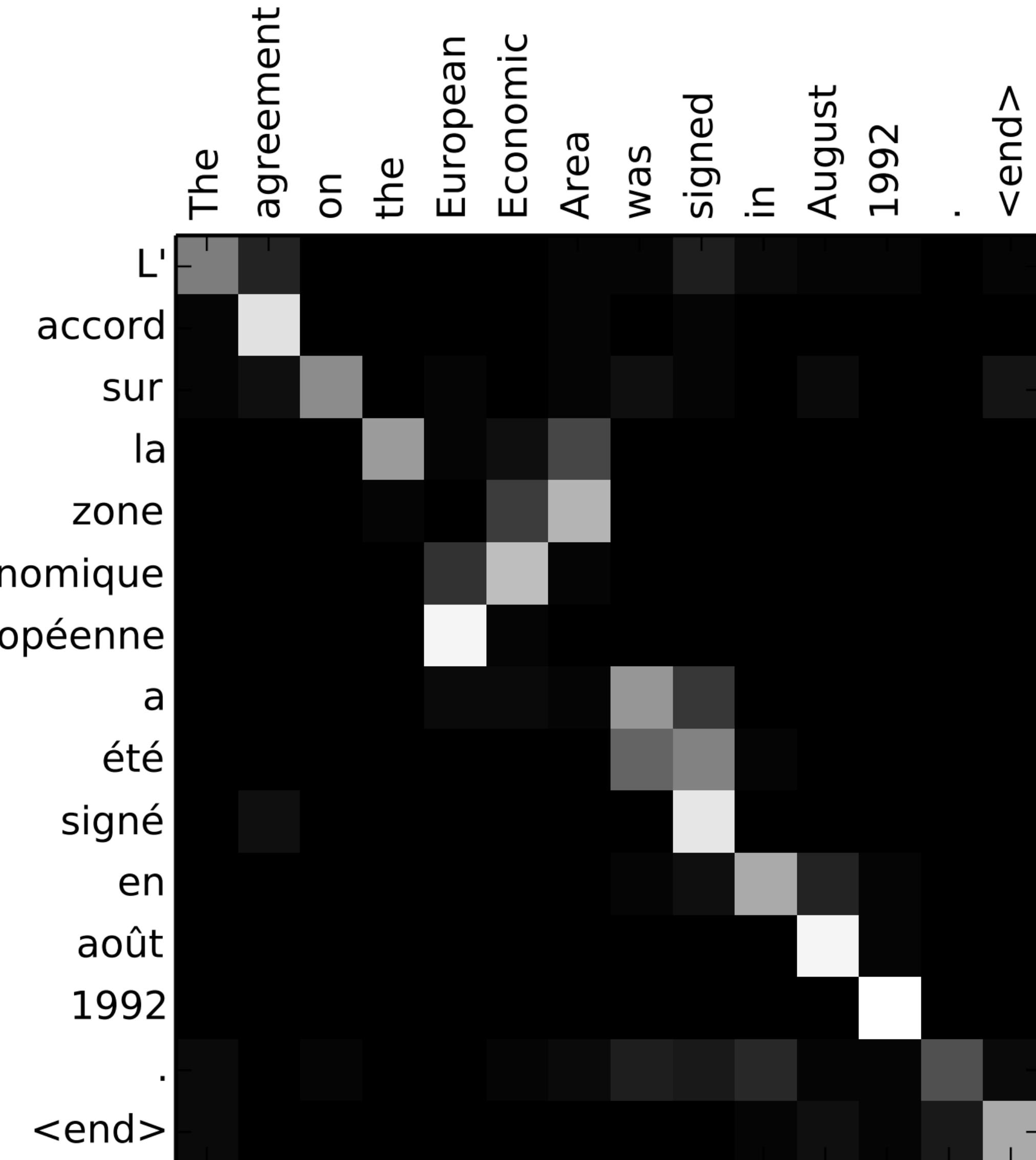
Attention

- ▶ Encoder hidden states capture contextual source word identity



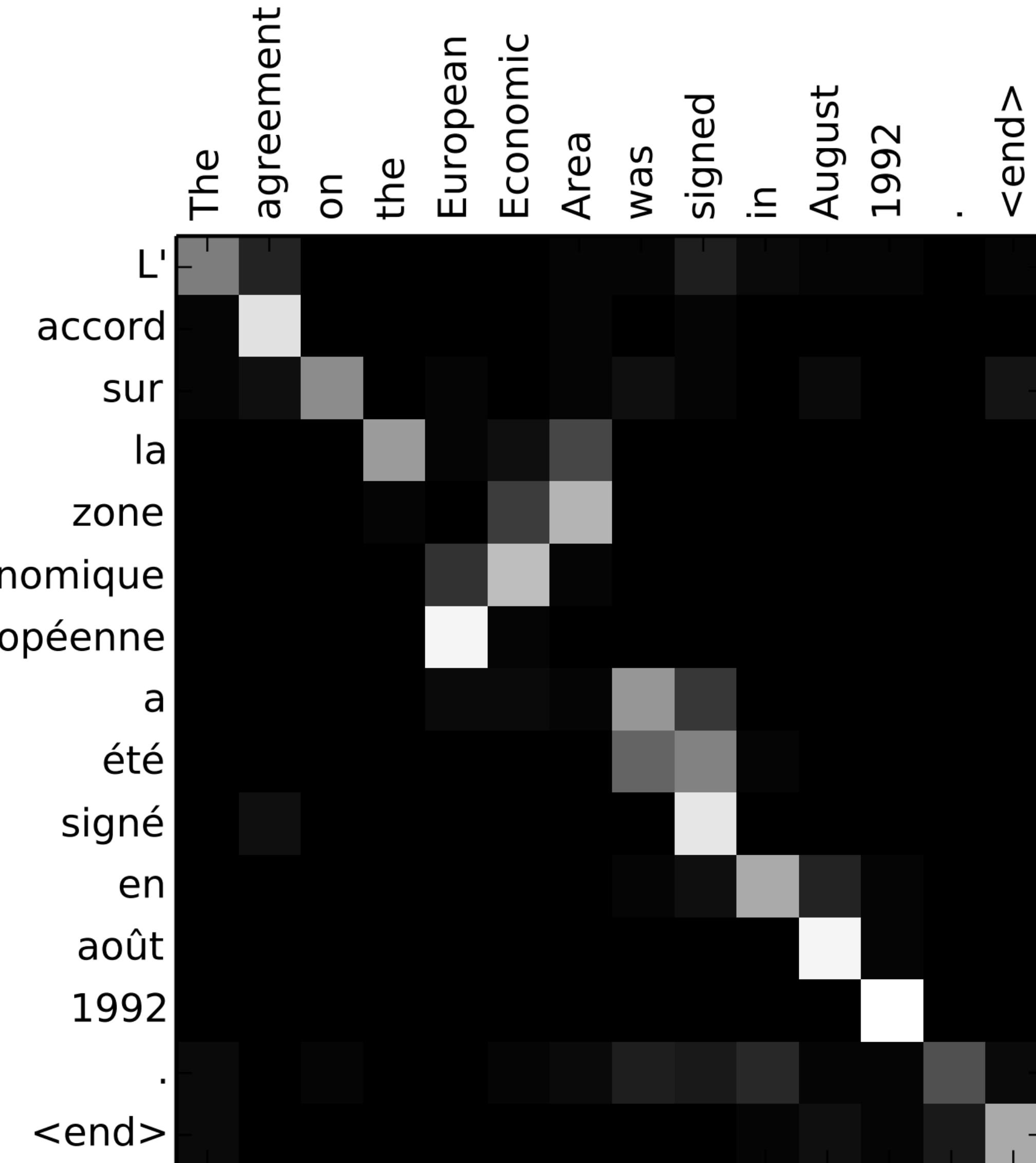
Attention

- ▶ Encoder hidden states capture contextual source word identity
- ▶ Decoder hidden states are now mostly responsible for selecting what to attend to

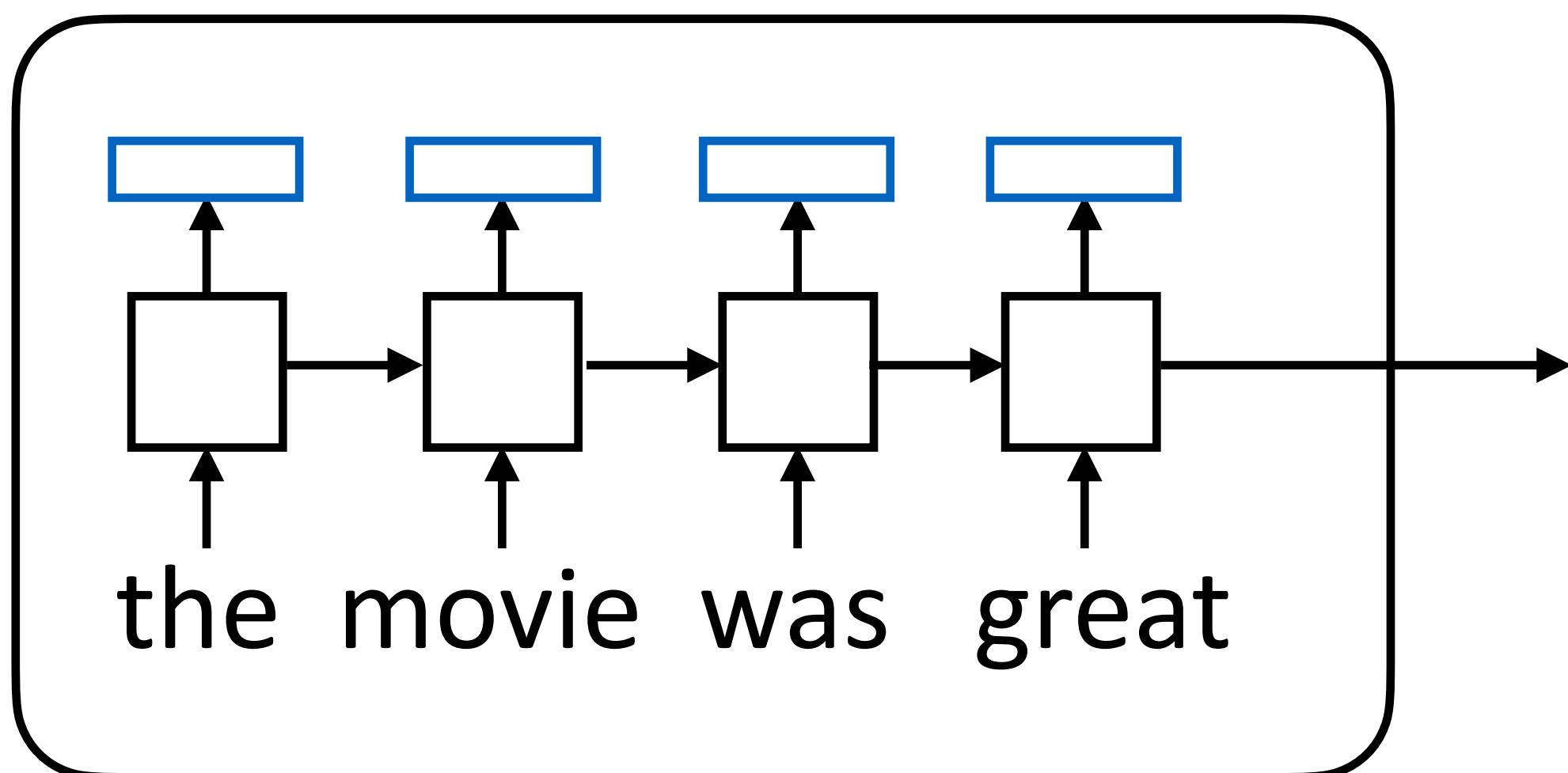


Attention

- ▶ Encoder hidden states capture contextual source word identity
- ▶ Decoder hidden states are now mostly responsible for selecting what to attend to
- ▶ Doesn't take a complex hidden state to walk monotonically through a sentence and spit out word-by-word translations

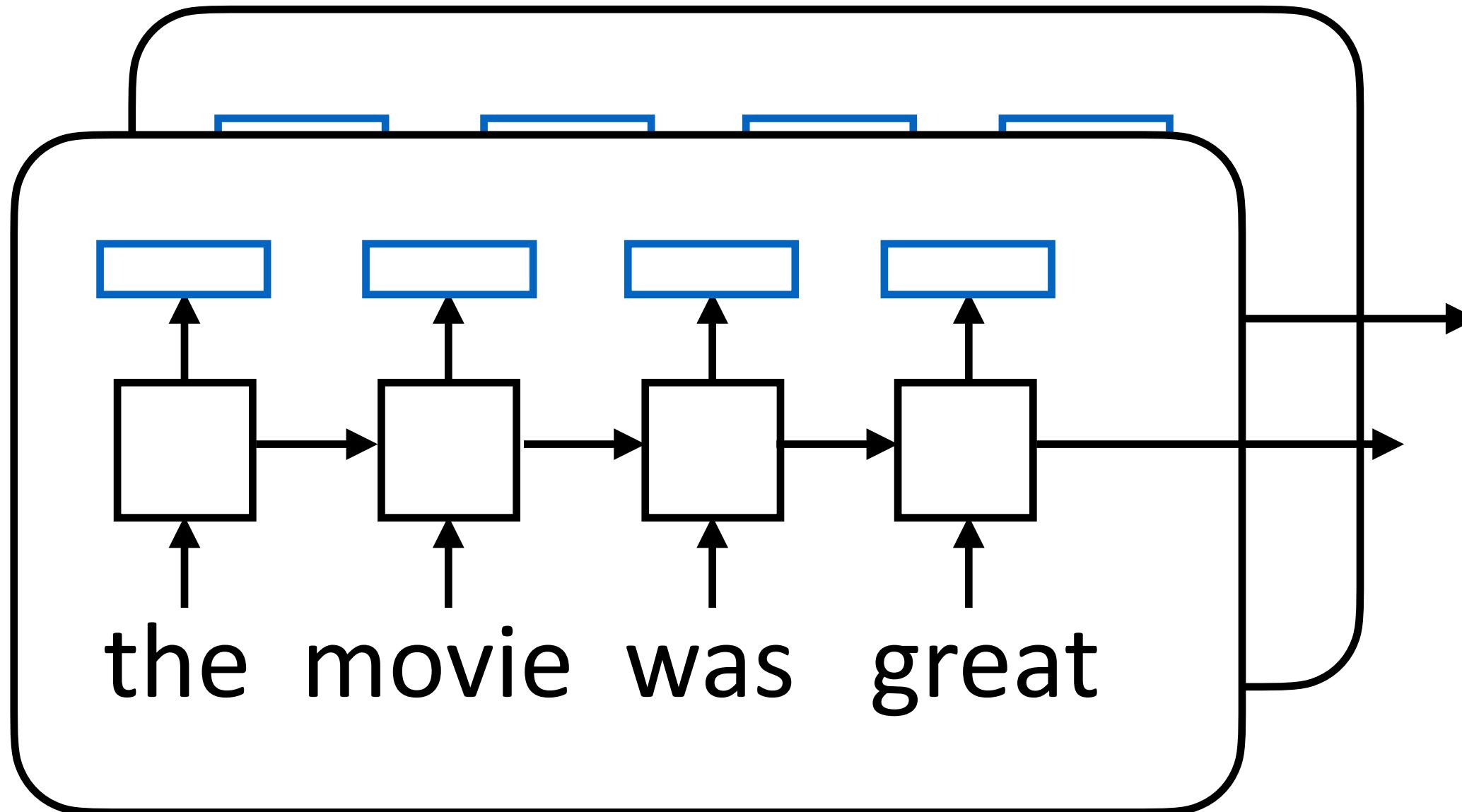


Batching Attention



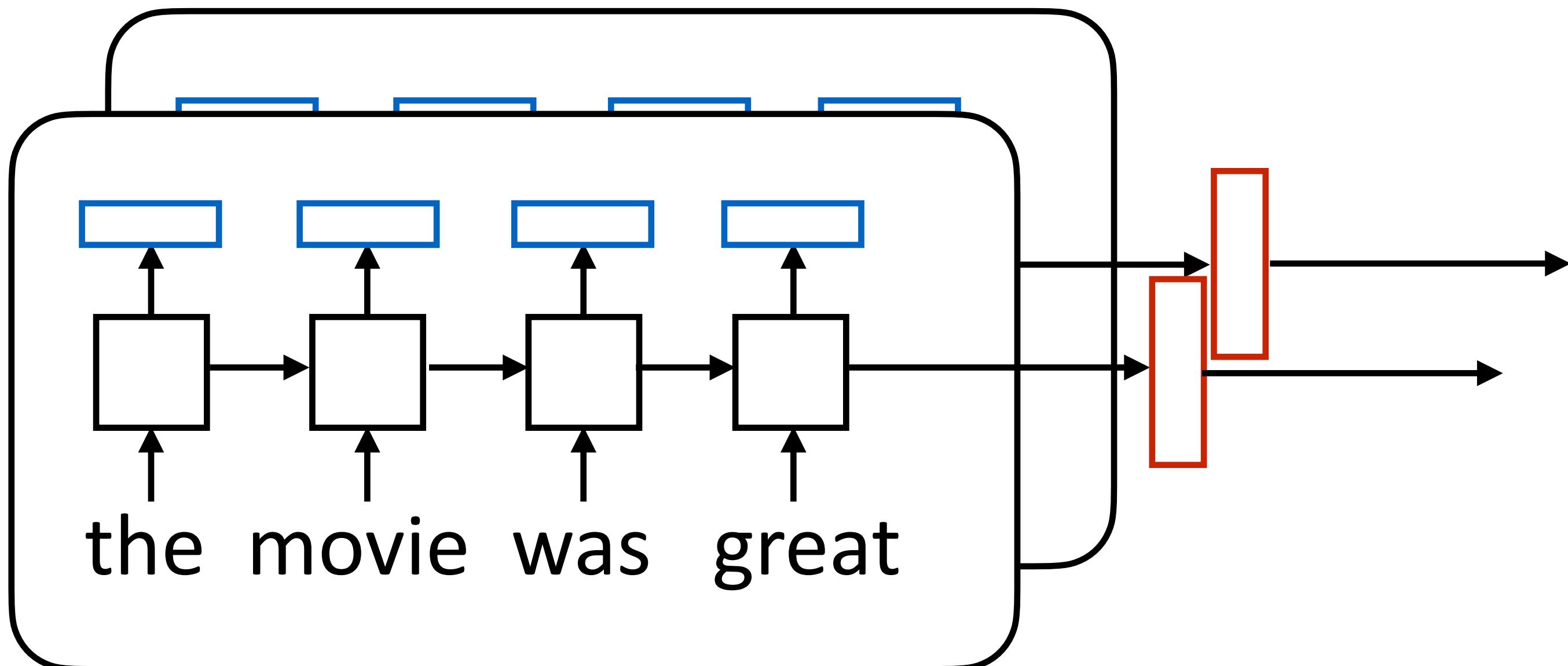
Batching Attention

token outputs: batch size x sentence length x dimension



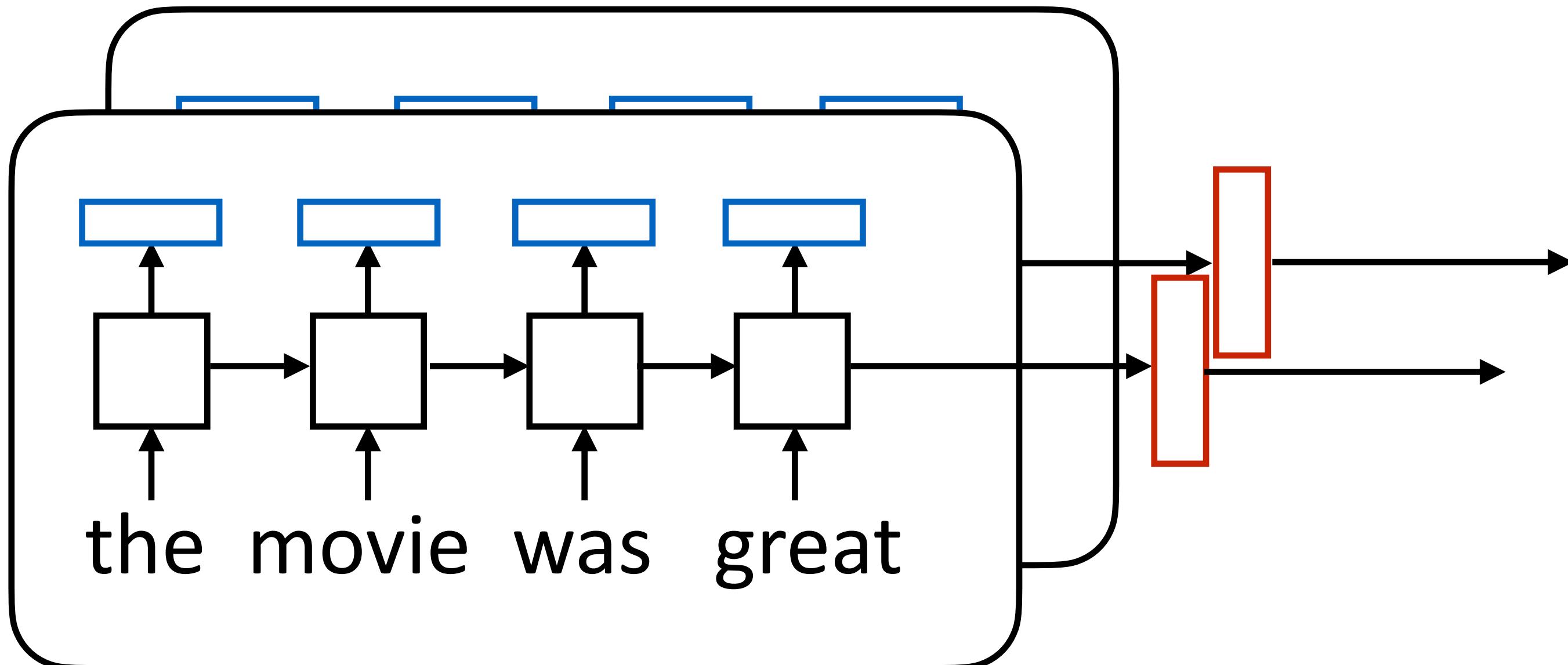
Batching Attention

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Batching Attention

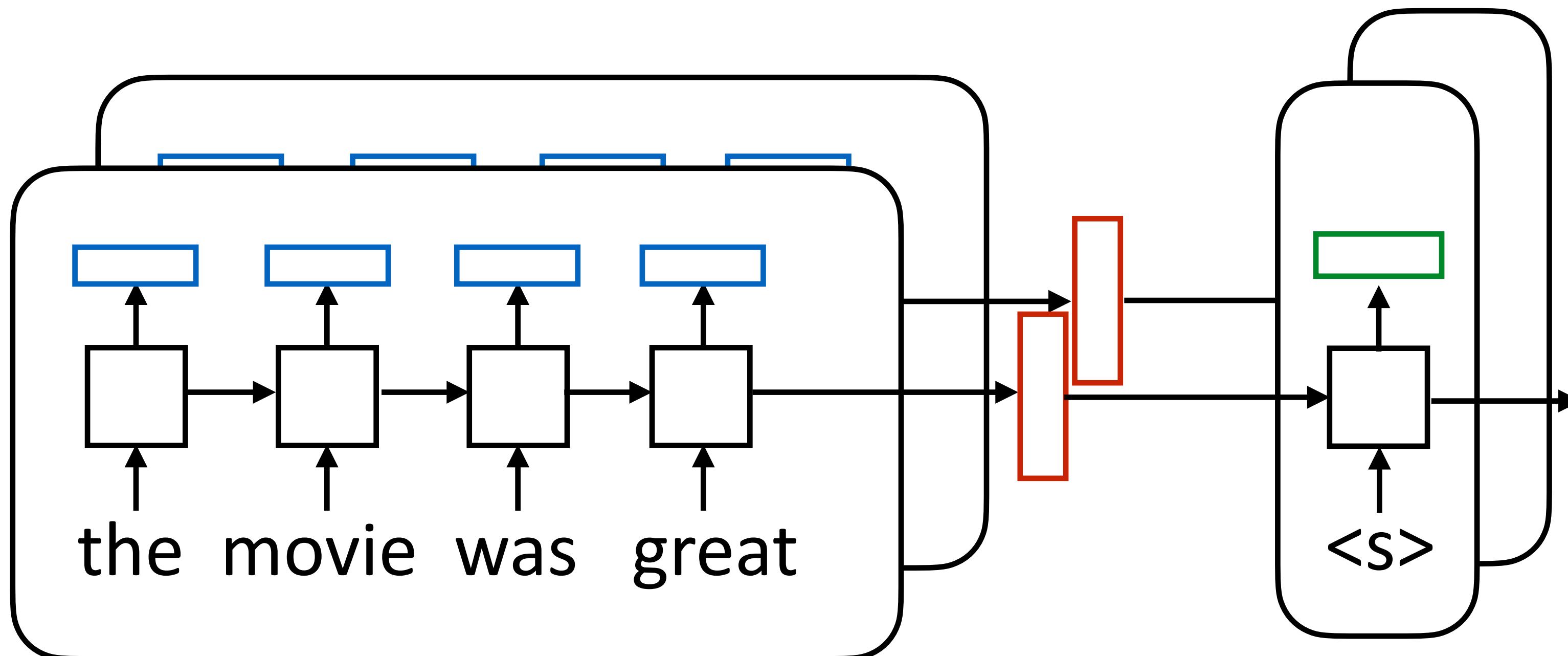
token outputs: batch size x sentence length x dimension



sentence outputs:
batch size x hidden size

Batching Attention

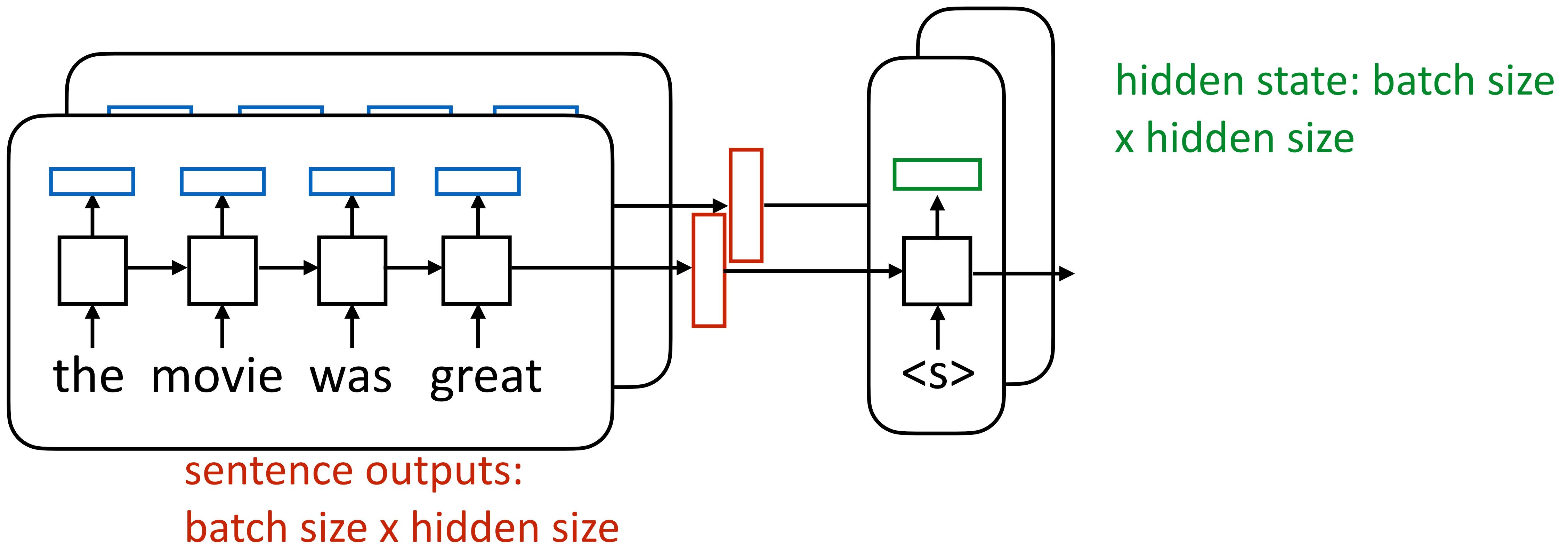
token outputs: batch size x sentence length x dimension



sentence outputs:
batch size x hidden size

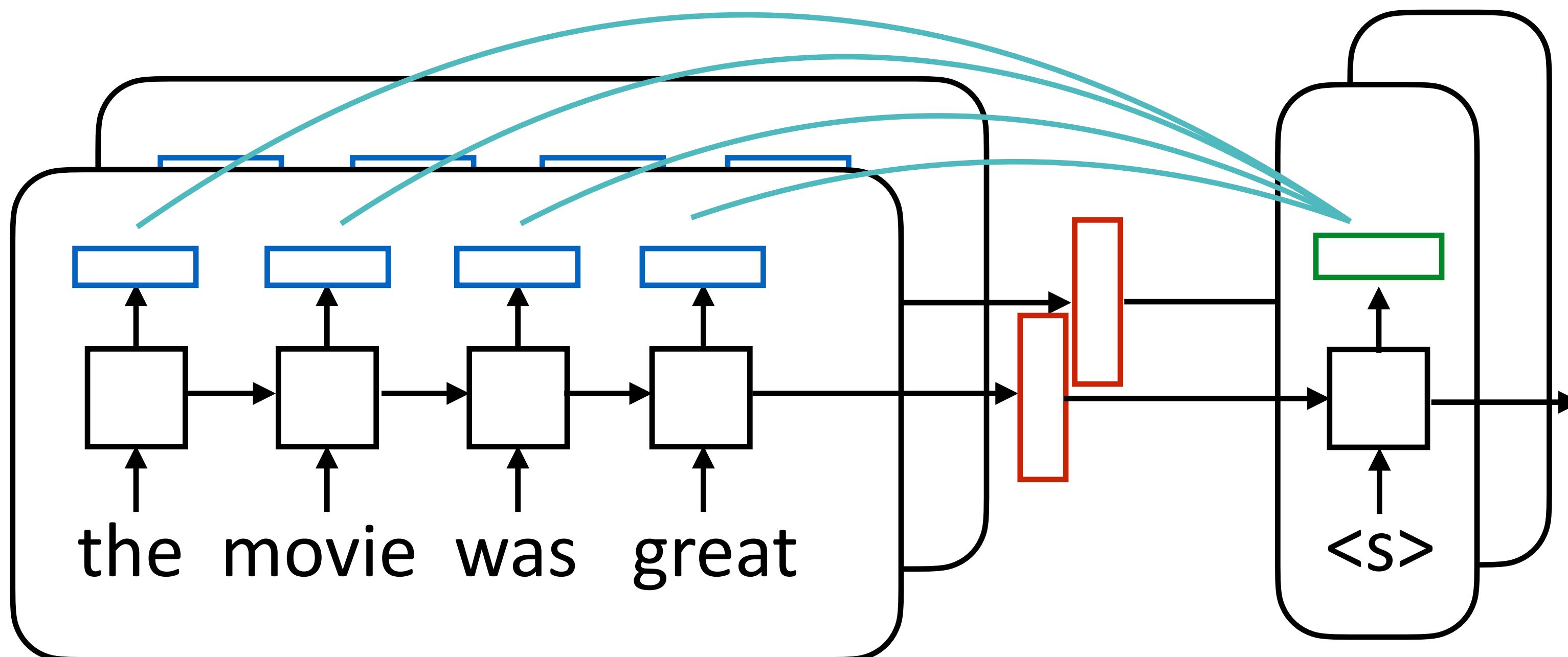
Batching Attention

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Batching Attention

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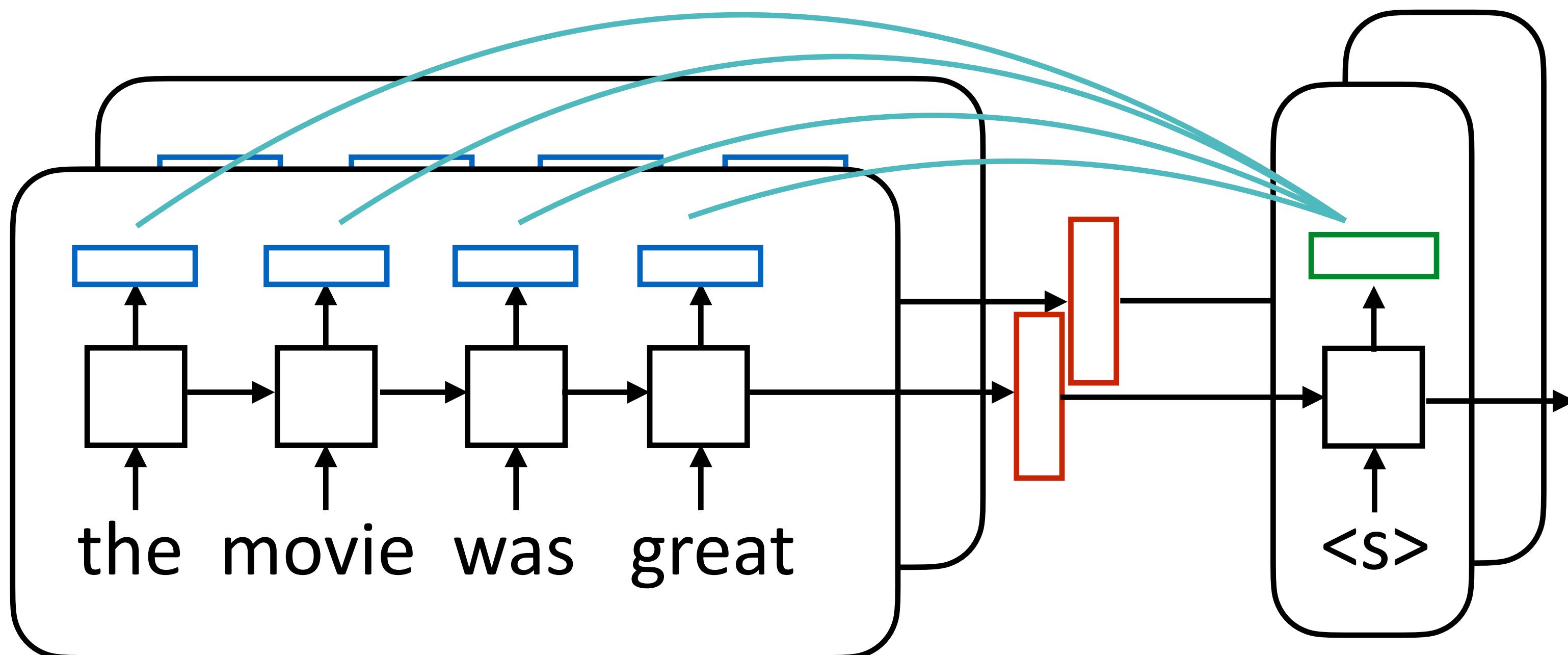


sentence outputs:
batch size x hidden size

hidden state: batch size
x hidden size

Batching Attention

token outputs: batch size x sentence length x dimension



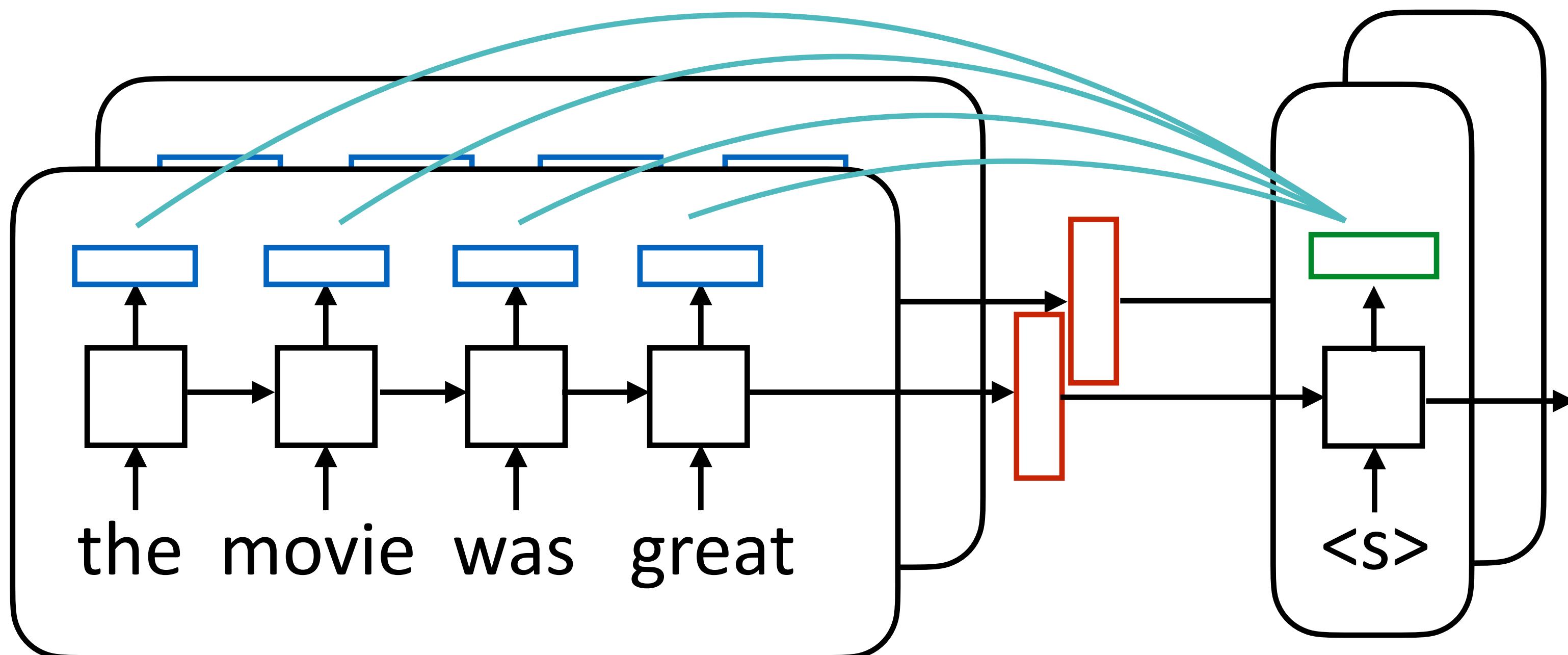
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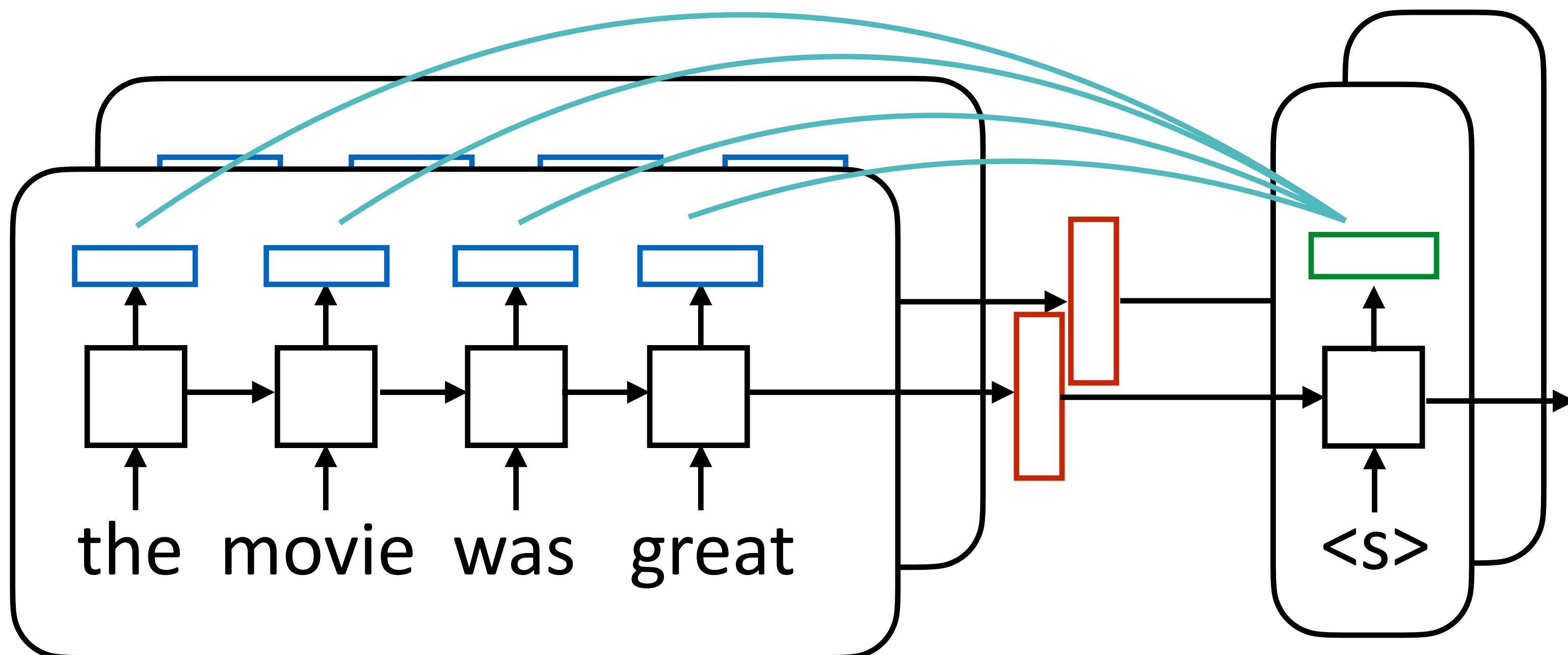
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sentence outputs:
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attention scores = batch size x sentence length

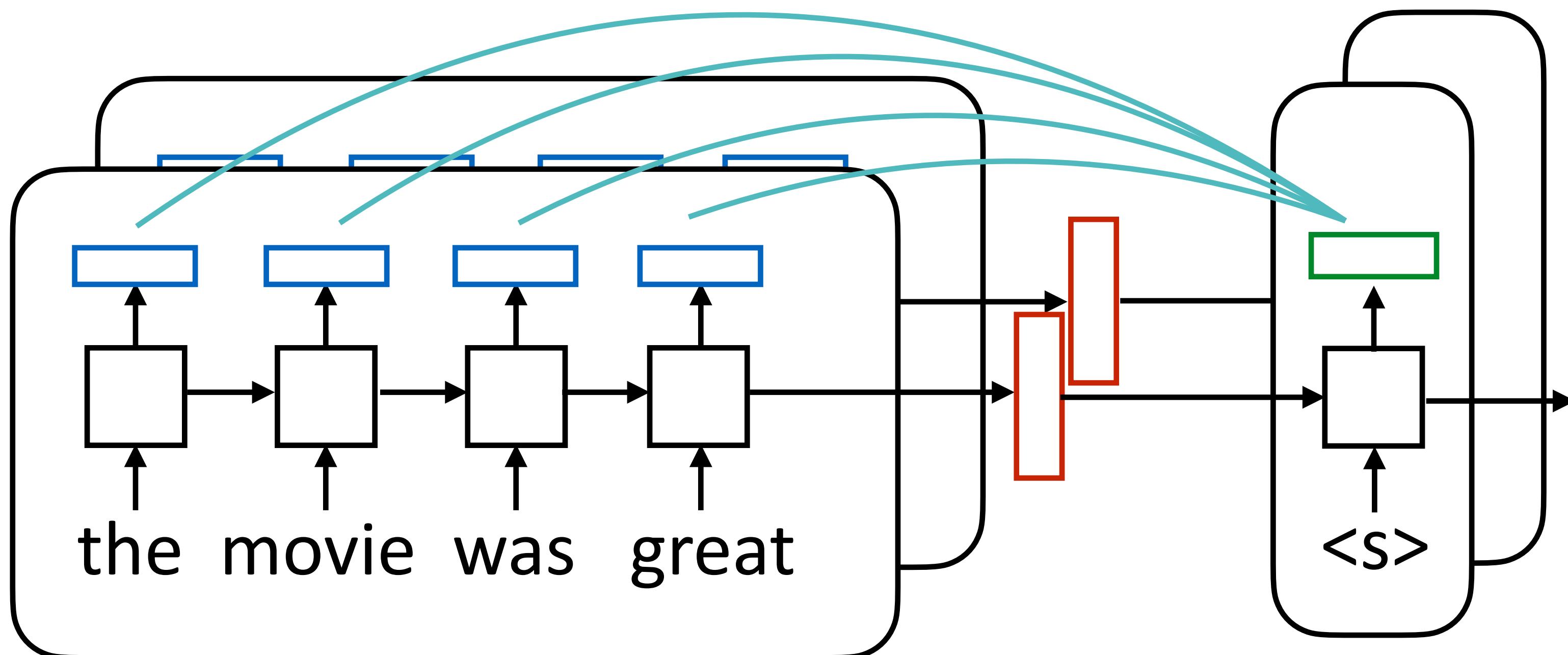
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attention scores = batch size x sentence length

$c = \text{batch size} \times \text{hidden size}$

$$c_i = \sum_j \alpha_{ij} h_j$$

hidden state: batch size
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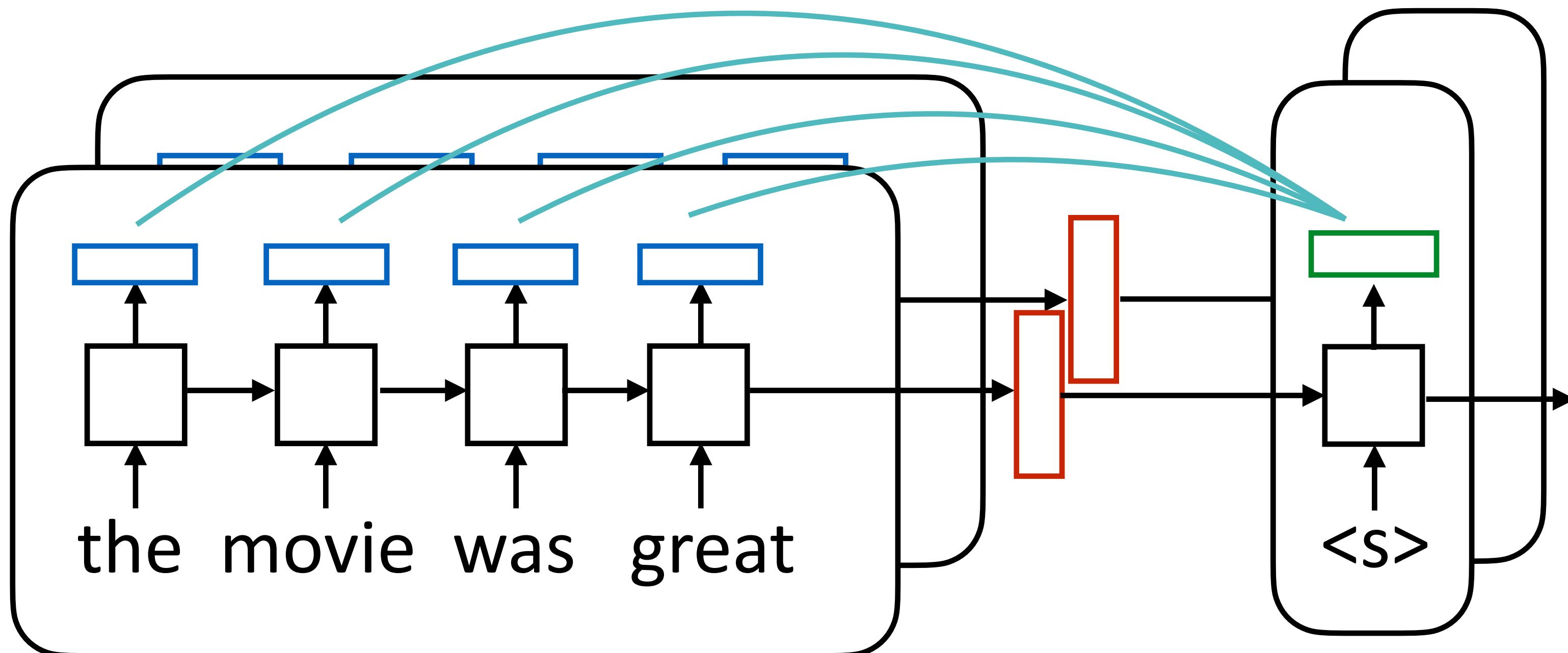
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Luong et al. (2015)

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- Make sure tensors are the right size!

Luong et al. (2015)

Results

Luong et al. (2015)
Chopra et al. (2016)
Jia and Liang (2016)

Results

- ▶ Machine translation: BLEU score of 14.0 on English-German -> 16.8 with attention, 19.0 with smarter attention (we'll come back to this later)

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- ▶ Summarization/headline generation: bigram recall from 11% -> 15%
- ▶ Semantic parsing: ~30% accuracy -> 70+% accuracy on Geoquery

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Chopra et al. (2016)

Jia and Liang (2016)

Copying Input/Pointers

Unknown Words

en: The ecotax portico in Pont-de-Buis , ... [truncated] ..., was taken down on Thursday morning

fr: Le portique écotaxe de Pont-de-Buis , ... [truncated] ..., a été démonté jeudi matin

nn: Le unk de unk à unk , ... [truncated] ..., a été pris le jeudi matin

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$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$

from attention

from RNN
hidden state

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- Still can only generate from the vocabulary

Learning to Copy

- ▶ Suppose we only care about being able to copy words from the input (maybe we're summarizing a document)

the movie was, despite its many flaws, great → *the movie was great*

- ▶ Standard models predict from a vocabulary, but here the vocabulary changes with every new input

On Thursday, police arrested two suspects → *police arrested two*

- ▶ Predicting from a fixed vocabulary doesn't make sense here

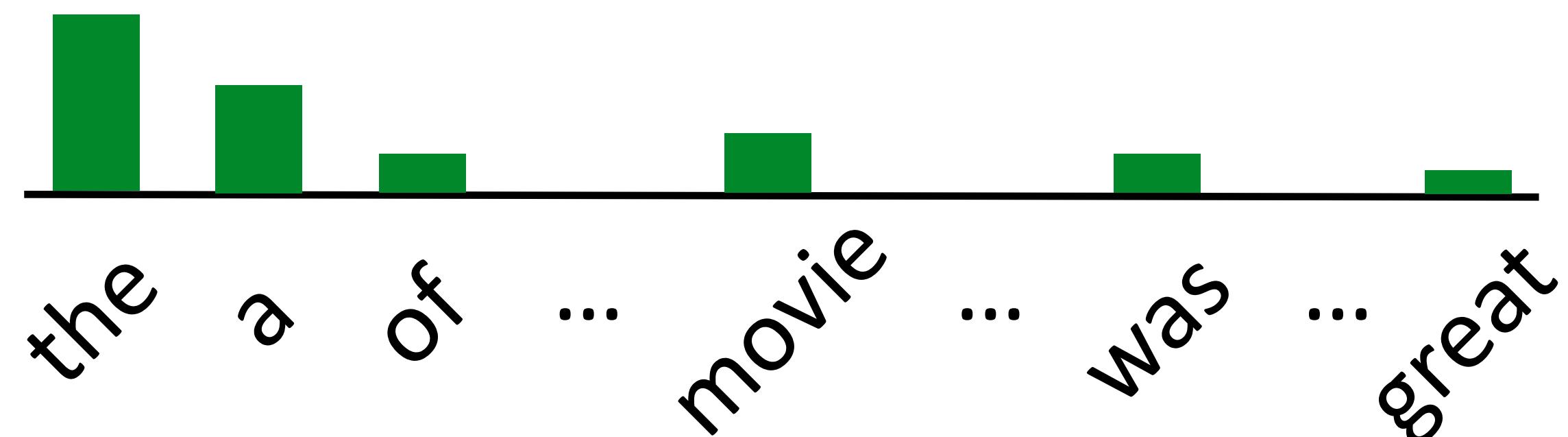
Output Space

- ▶ Let $[x_1, \dots, x_n]$ be the set of words in the input
- ▶ Rather than distribution over the vocabulary, predict distribution over the x_i
- ▶ **Key observation:** this is exactly the same thing that attention gives us!
- ▶ Instead of a traditional softmax layer, **we use attention to predict the output directly.**
- ▶ This is called a pointer network (or a copy mechanism)

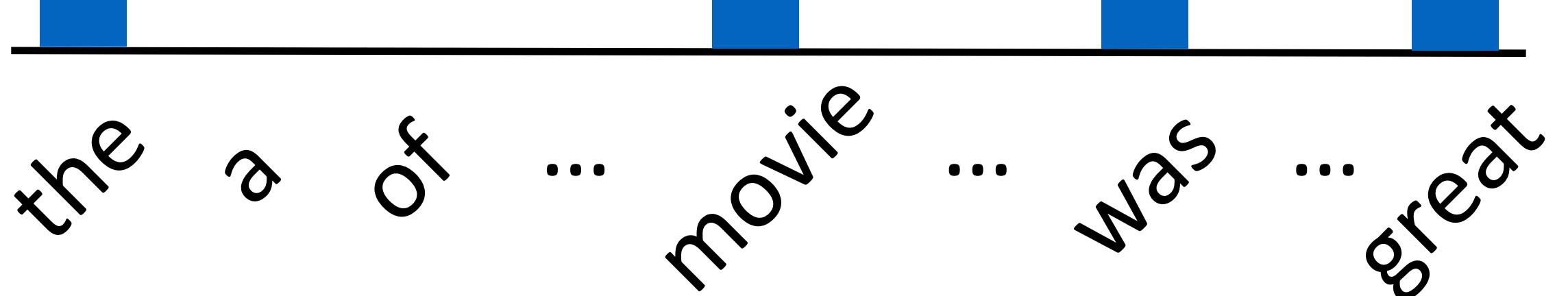
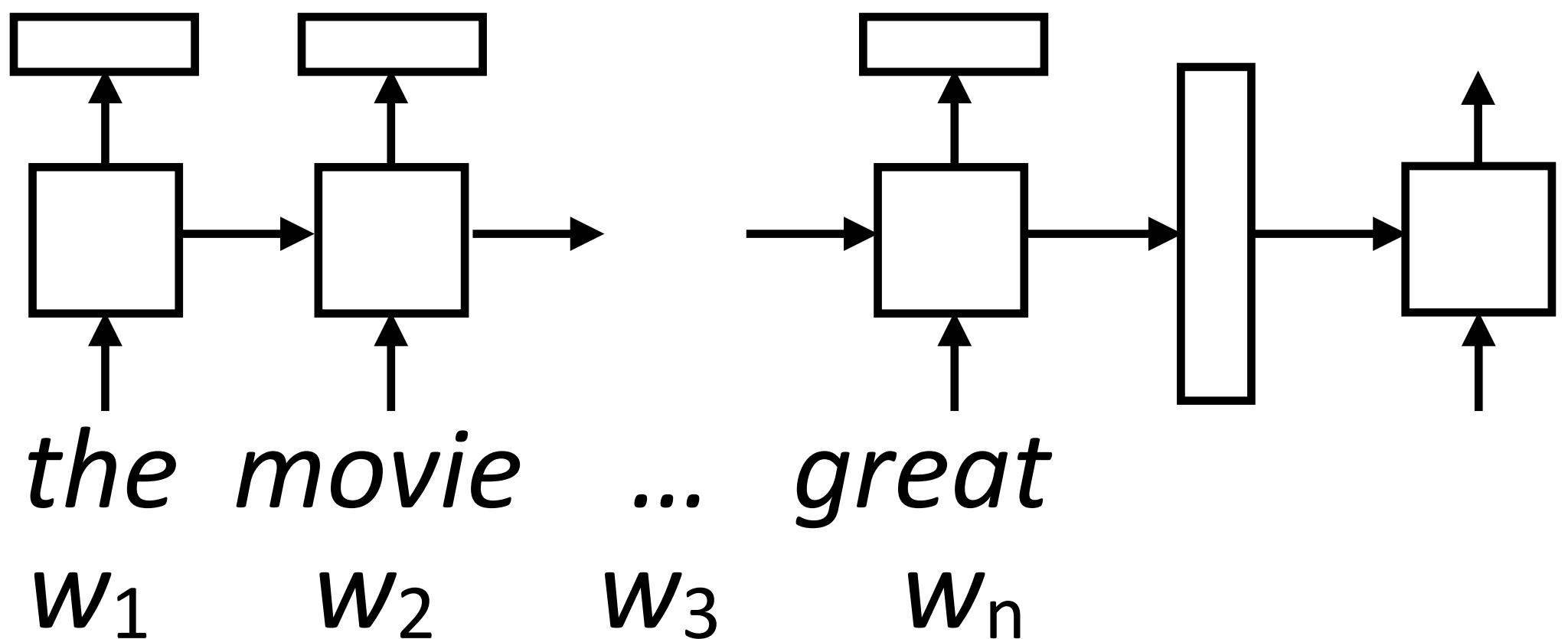
Pointer Networks

$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$

- ▶ Standard decoder (P_{vocab}): softmax over vocabulary, all words get >0 prob
- ▶ Pointer network: predict from *source words* instead of *target vocab*



$$P_{\text{pointer}}(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) \propto \begin{cases} \exp(h_j^\top V \bar{h}_i) & \text{if } y_i = w_j \\ 0 & \text{otherwise} \end{cases}$$

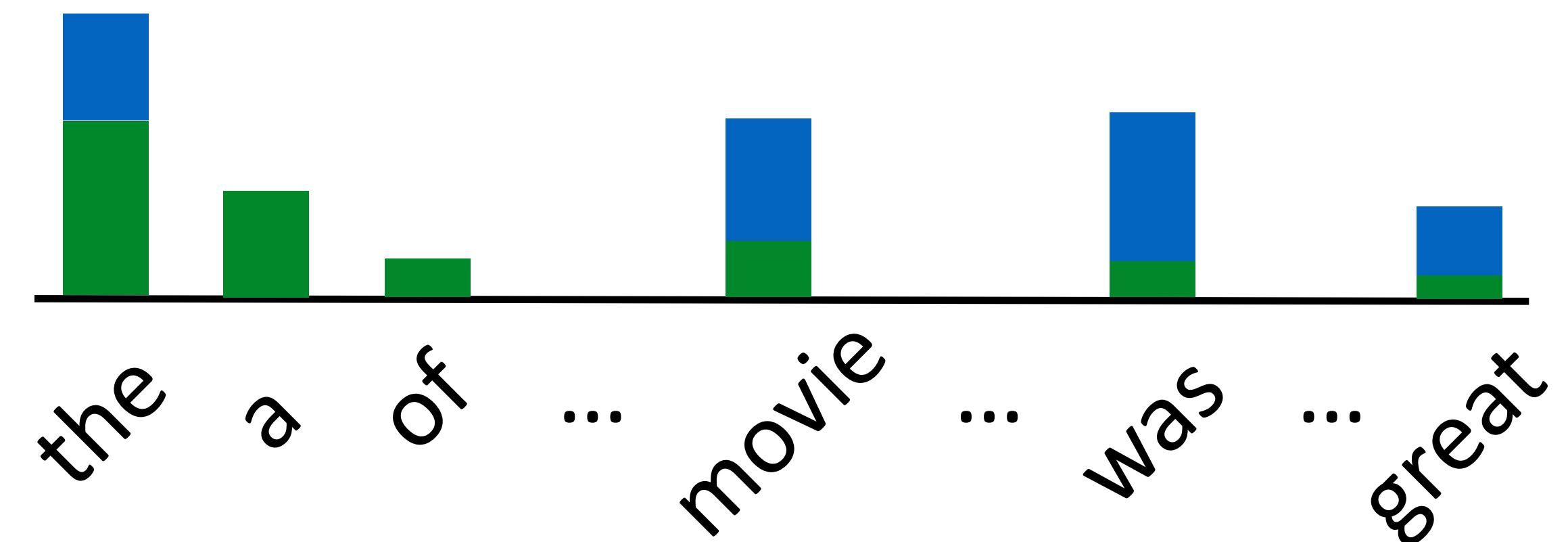


Pointer Generator Mixture Models

- ▶ Define the decoder model as a mixture model of the P_{vocab} and P_{pointer} models (previous slide)

$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = P(\text{copy})P_{\text{pointer}} + (1 - P(\text{copy}))P_{\text{vocab}}$$

- ▶ Predict $P(\text{copy})$ based on decoder state, input, etc.
- ▶ Marginalize over copy variable during training and inference
- ▶ Model will be able to both generate and copy, flexibly adapt between the two



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- ▶ Vocabulary contains “normal” vocab as well as words in input. Normalizes over both of these:

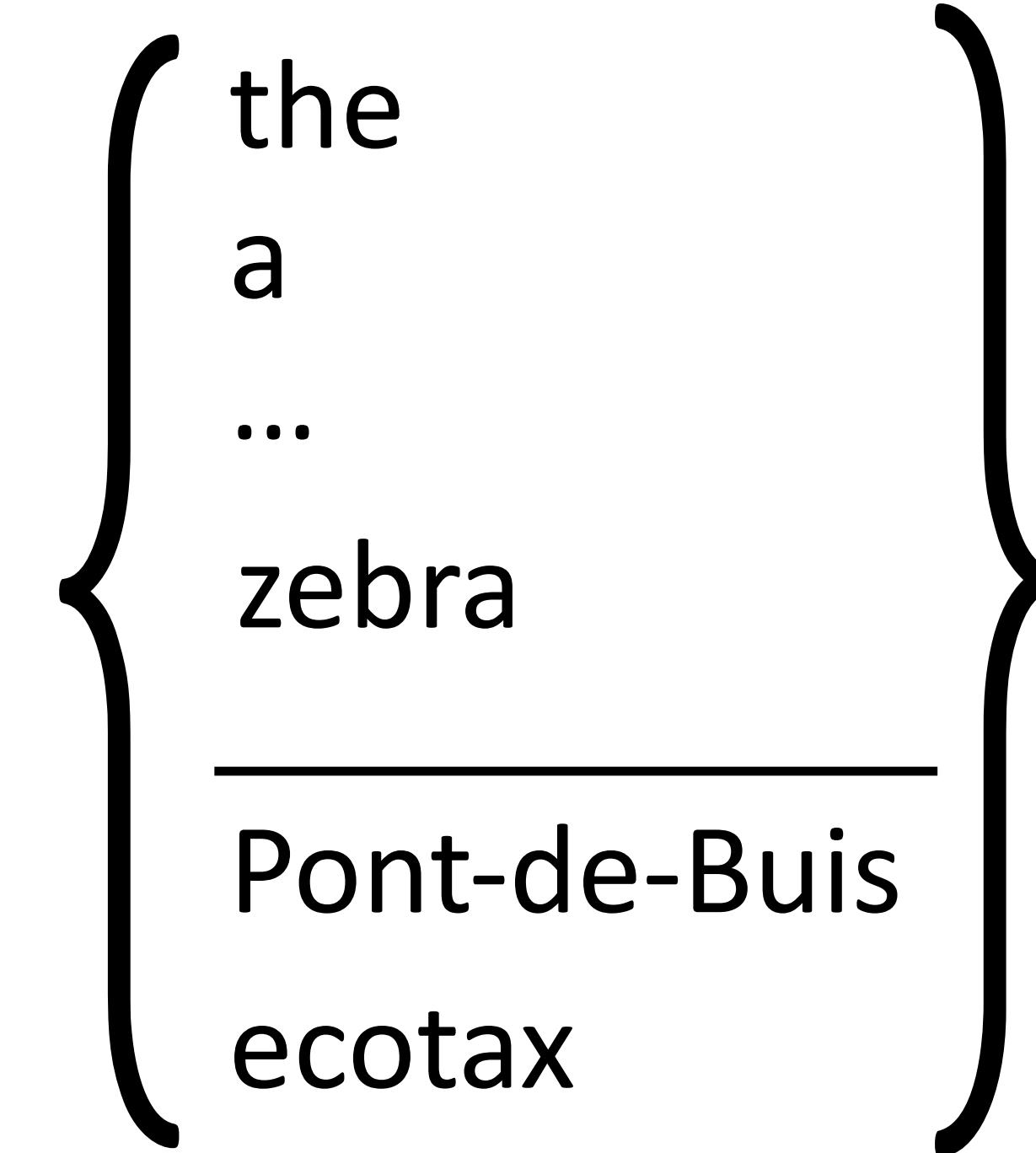
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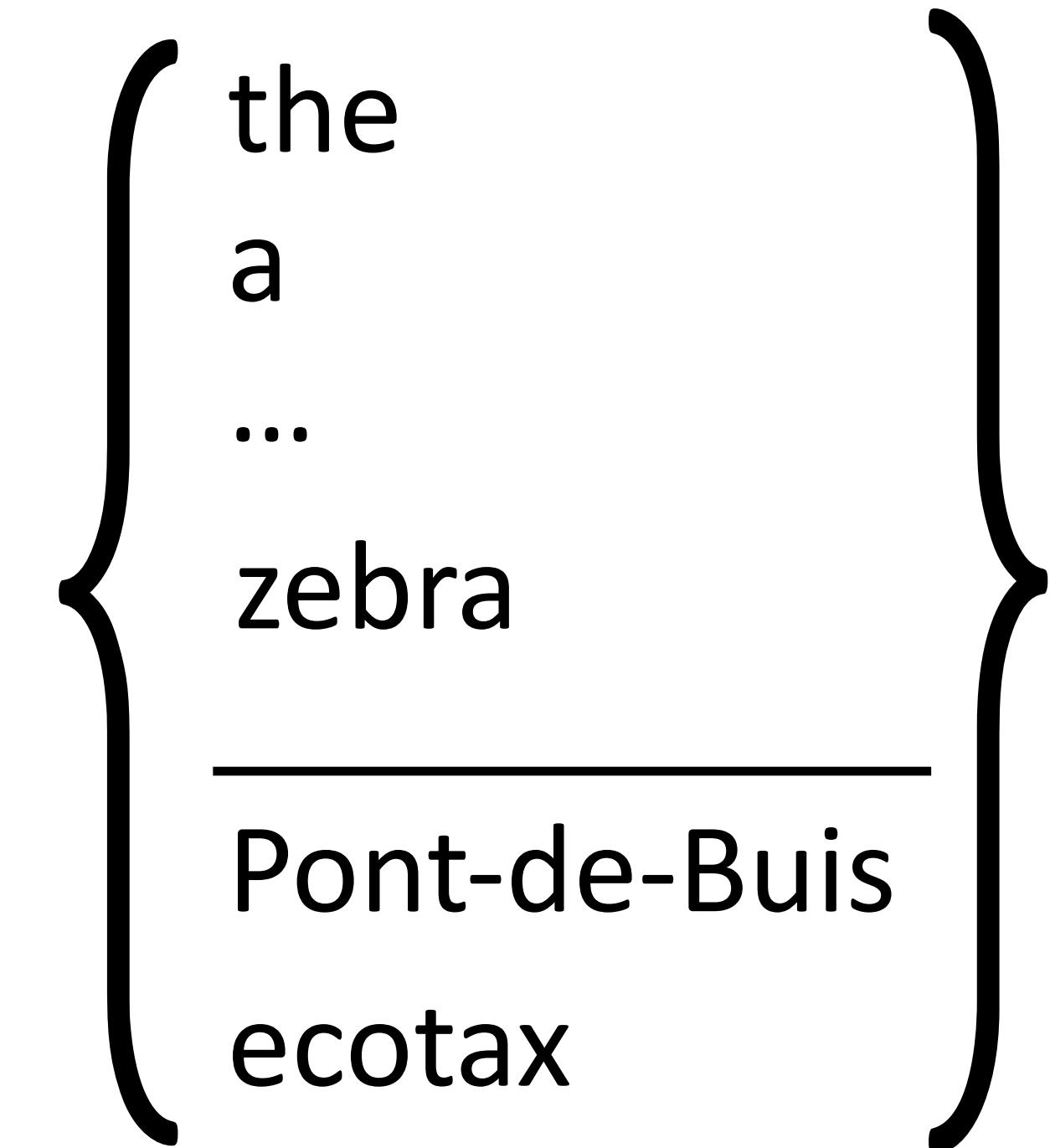
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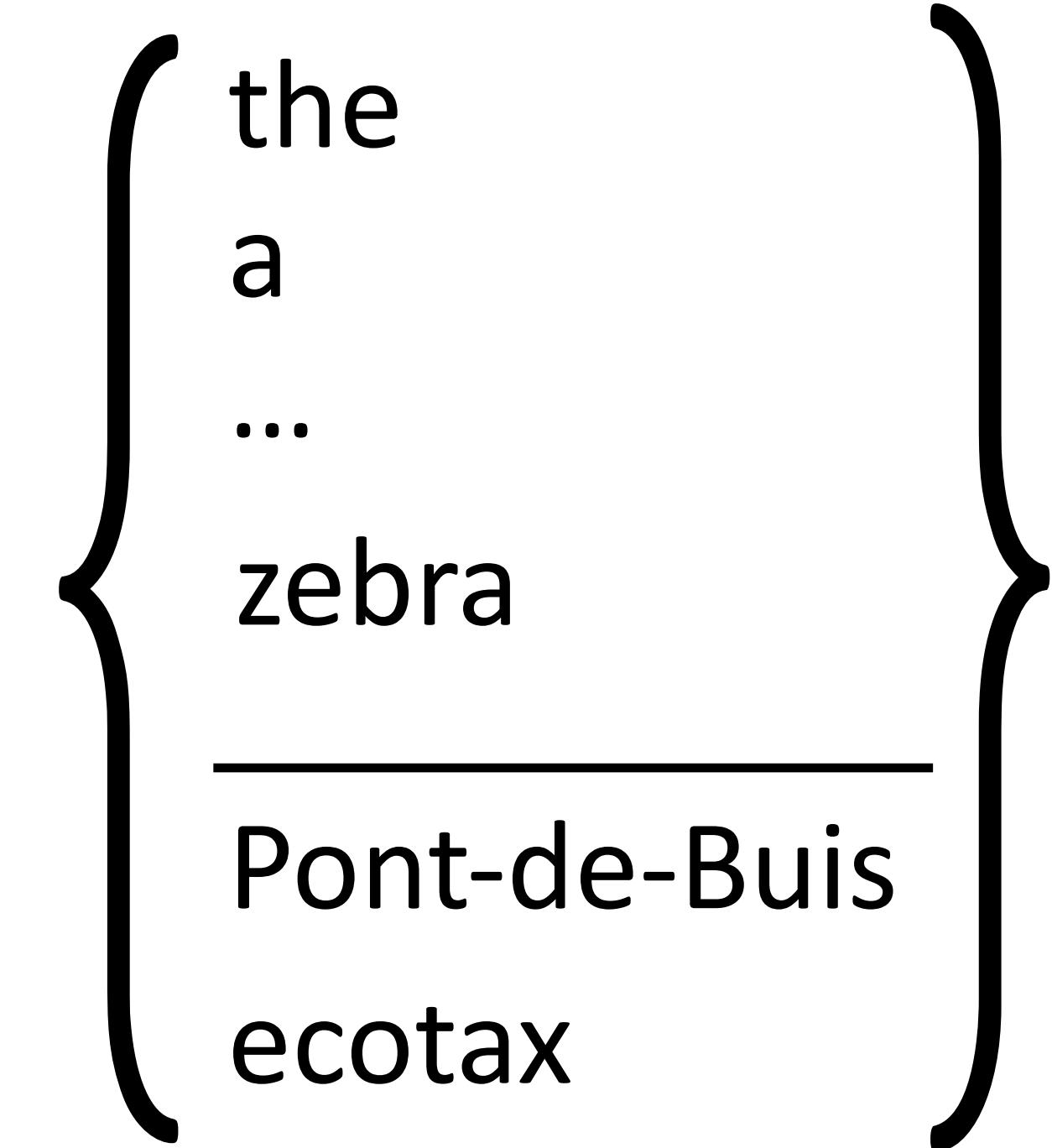
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- Bilinear function of input representation + output hidden state



Results

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

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- ▶ For semantic parsing, copying tokens from the input (texas) can be very useful

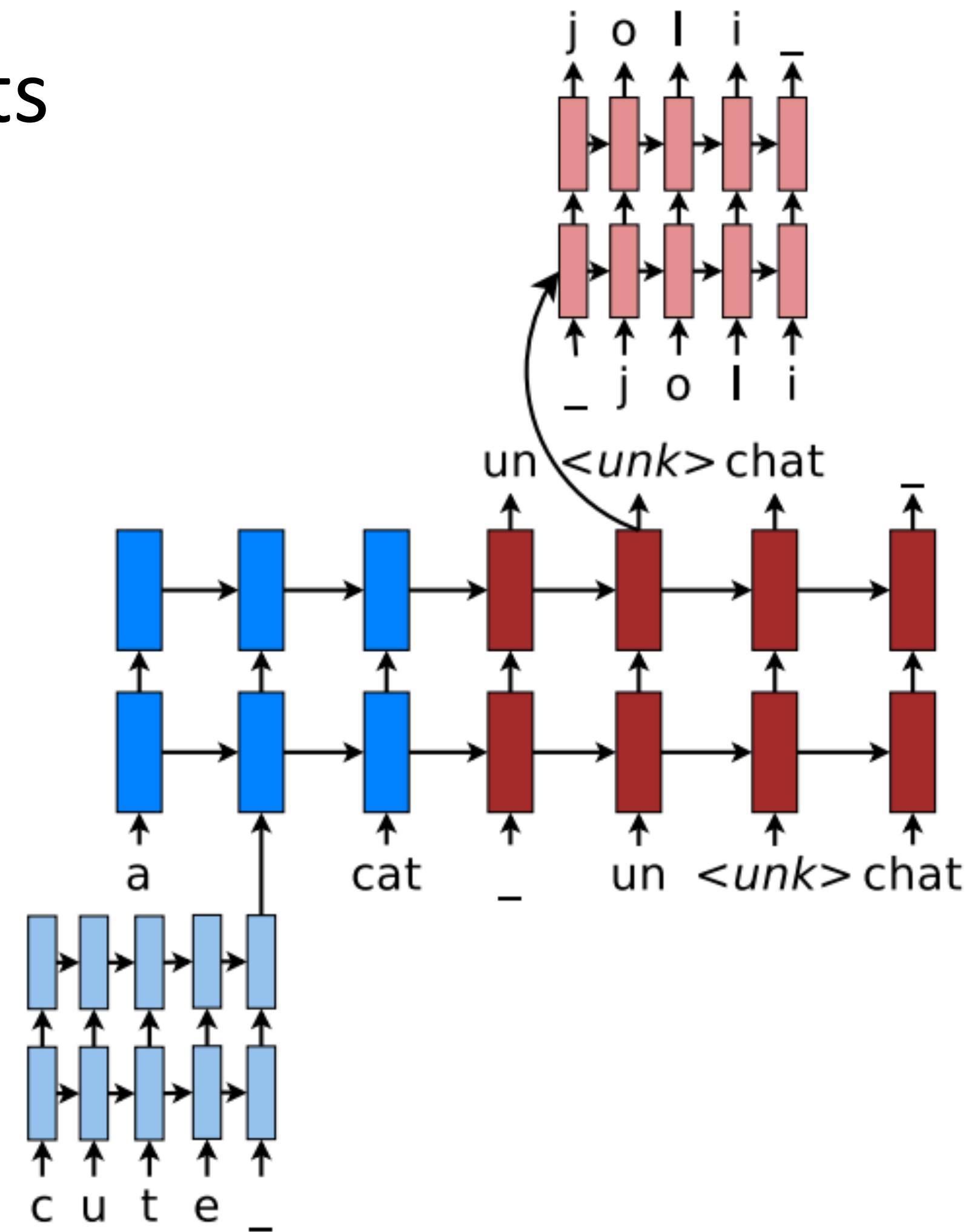
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- ▶ For semantic parsing, copying tokens from the input (texas) can be very useful
- ▶ In many settings, attention can roughly do the same things as copying

Rare Words: Character Models

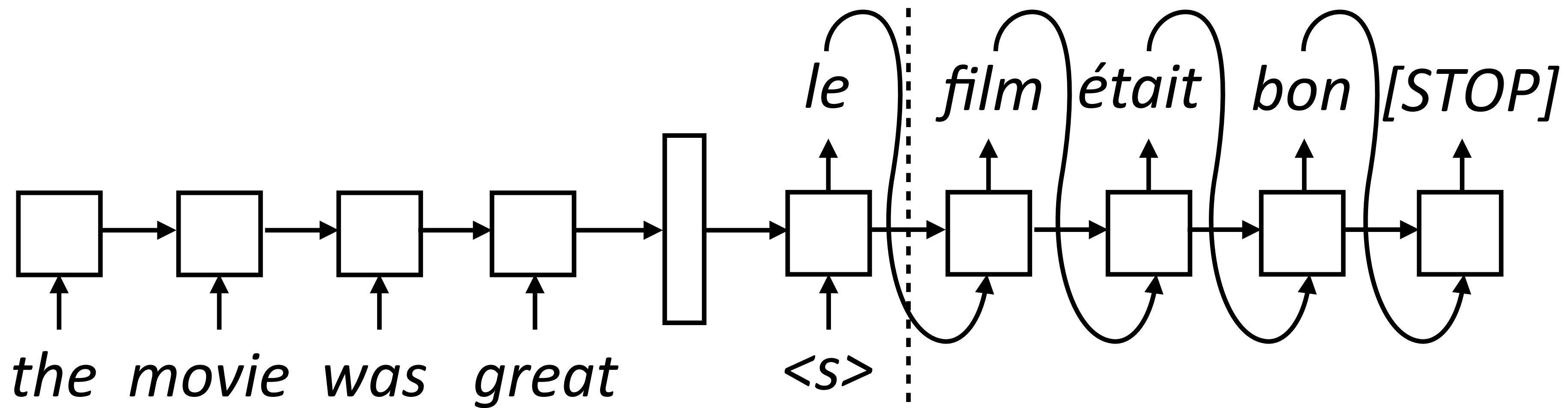
- ▶ If we predict an unk token, generate the results from a character LSTM
- ▶ Can potentially transliterate new concepts, but architecture is more complicated and slower to train
- ▶ We will talk about alternatives to this when we talk about machine translation



Decoding Strategies

Greedy Decoding

- ▶ Generate next word conditioned on previous word as well as hidden state



- ▶ During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state. This is **greedy decoding**

$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W\bar{h}) \quad (\text{or attention/copying/etc.})$$

$$y_{\text{pred}} = \text{argmax}_y P(y | \mathbf{x}, y_1, \dots, y_{i-1})$$

Problems with Greedy Decoding

- ▶ Only returns one solution, and it may not be optimal
- ▶ Can address this with **beam search**, which usually works better...but even beam search may not find the correct answer! (max probability sequence)

Model	Beam-10	
	BLEU	#Search err.
LSTM*	28.6	58.4%
SliceNet*	28.8	46.0%
Transformer-Base	30.3	57.7%
Transformer-Big*	31.7	32.1%

“Problems” with Beam Decoding

- ▶ For machine translation, the highest probability sequence is often the empty string! (>50% of the time)

Search	BLEU	Ratio	#Search errors	#Empty
Greedy	29.3	1.02	73.6%	0.0%
Beam-10	30.3	1.00	57.7%	0.0%
Exact	2.1	0.06	0.0%	51.8%

- ▶ Beam search results in *fortuitous search errors* that avoid these bad solutions

Sampling

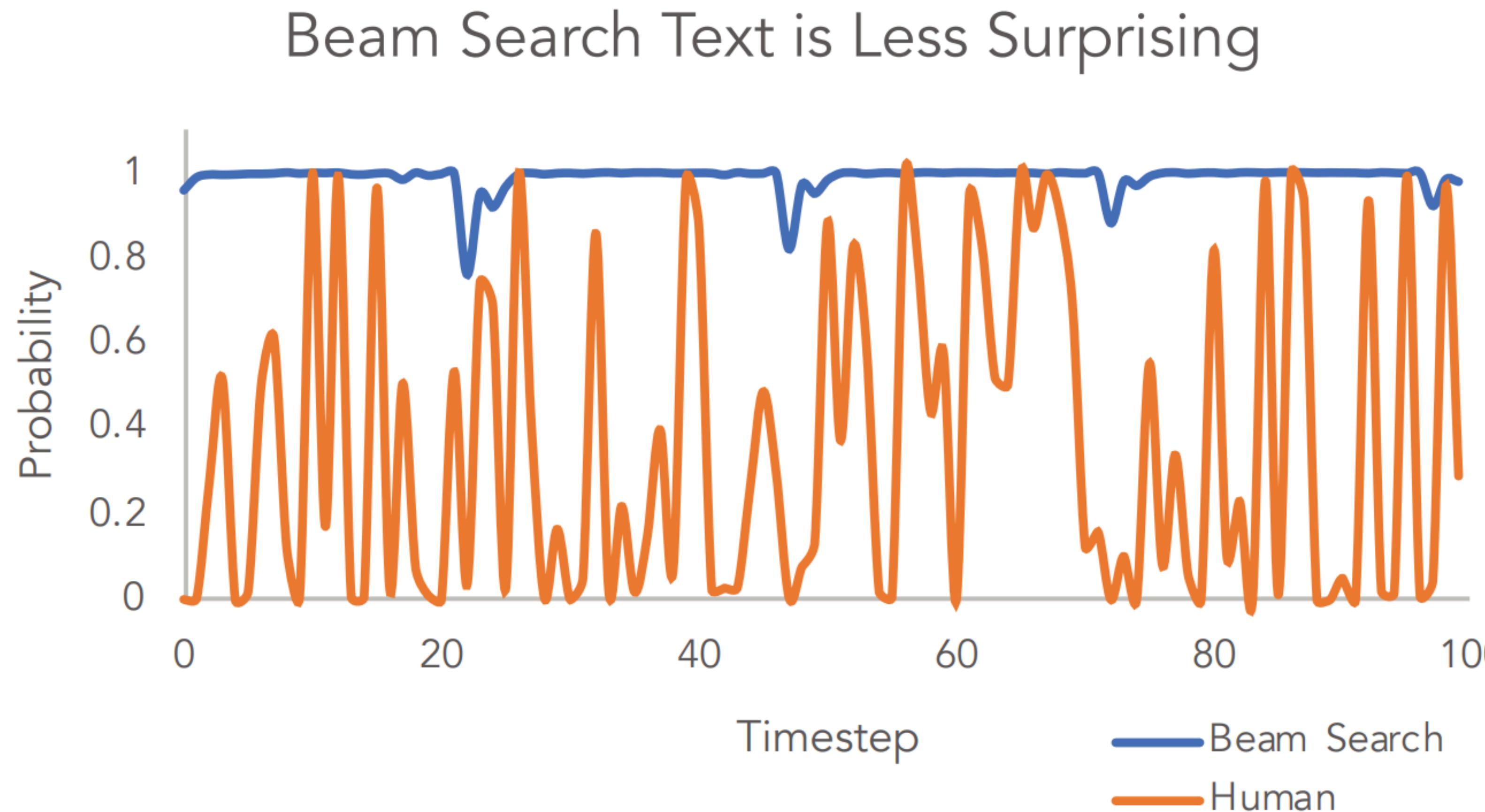
- ▶ Beam search may give many similar sequences, and these actually may be *too close* to the optimal. Can sample instead:

$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W\bar{h})$$

$$y_{\text{sampled}} \sim P(y | \mathbf{x}, y_1, \dots, y_{i-1})$$

- ▶ Text *degeneration*: greedy solution can be uninteresting / vacuous for various reasons. Sampling can help.

Beam Search vs. Sampling



Beam Search vs. Sampling

- ▶ These are samples from an unconditioned language model (not seq2seq model)

Context: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Beam Search, $b=32$:

"The study, published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS), was conducted by researchers from the Universidad Nacional Autónoma de México (UNAM) and the Universidad Nacional Autónoma de México (UNAM/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de México/Universidad Nacional Autónoma de ...")

Pure Sampling:

They were cattle called **Bolivian Cavalleros**; they live in a remote desert **uninterrupted by town**, and they speak **huge, beautiful, paradisiacal Bolivian linguistic thing**. They say, 'Lunch, marge.' They don't tell what the lunch is," director Professor Chuperas Omwell told Sky News. "They've only been talking to scientists, like we're being interviewed by TV reporters. We don't even stick around to be interviewed by TV reporters. Maybe that's how they figured out that they're cosplaying as the Bolivian Cavalleros."

- ▶ Sampling is better but sometimes draws too far from the tail of the distribution

Decoding Strategies

- ▶ Greedy
- ▶ Beam search
- ▶ Sampling
- ▶ Nucleus or top-k sampling:
 - ▶ Nucleus: take the top p% (95%) of the distribution, sample from within that
 - ▶ Top-k: take the top k most likely words (k=5), sample from those

Generation Tasks



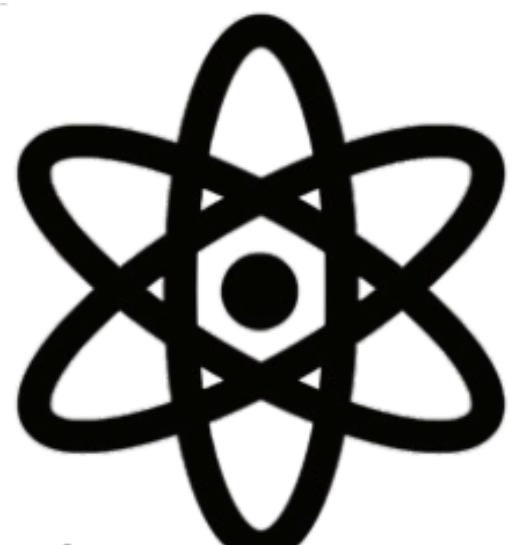
WebText



Beam Search, $b=16$



Pure Sampling



Nucleus, $p=0.95$

An unprecedented number of mostly young whales have become stranded on the West Australian coast since 2008.

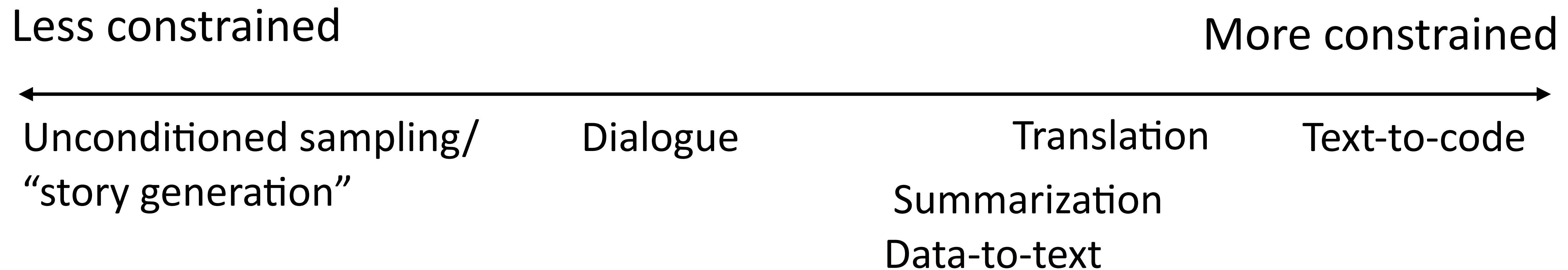
The number of stranded whales has increased by more than 50 per cent in the past year, with the number of stranded whales on the West Australian coast increasing by more than 50 per cent in the past year. The number of whales stranded on the West Australian coast has increased by more than 50 per cent in the past year, with the number of stranded whales on the West Australian coast increasing by more than 50 per cent in the past year.

The Australian Food Safety Authority has warned Australia's beaches may be revitalised this year because healthy seabirds and seals have been on the move. More than 50,000 seabirds, sea mammals and seahorses have been swept into the sea by the Holden CS118 and Adelaide Airport CS300 from 2013. A major white-bat and umidauda migration across Australia is under way in Australia for the first time, with numbers reaching an estimated 50,000.

There has been an unprecedented number of calves caught in the nets of whaling stations that operate in WA. Pilot whales continue to migrate to feeding grounds to feed their calves. They are now vulnerable due to the decline of wild populations; they are restricted to one breeding site each year. Image copyright Yoon Bo Kim But, with sharp decline in wild populations the size of the Petrels are shrinking and dwindling population means there will only be room for a few new fowl.

Generation Tasks

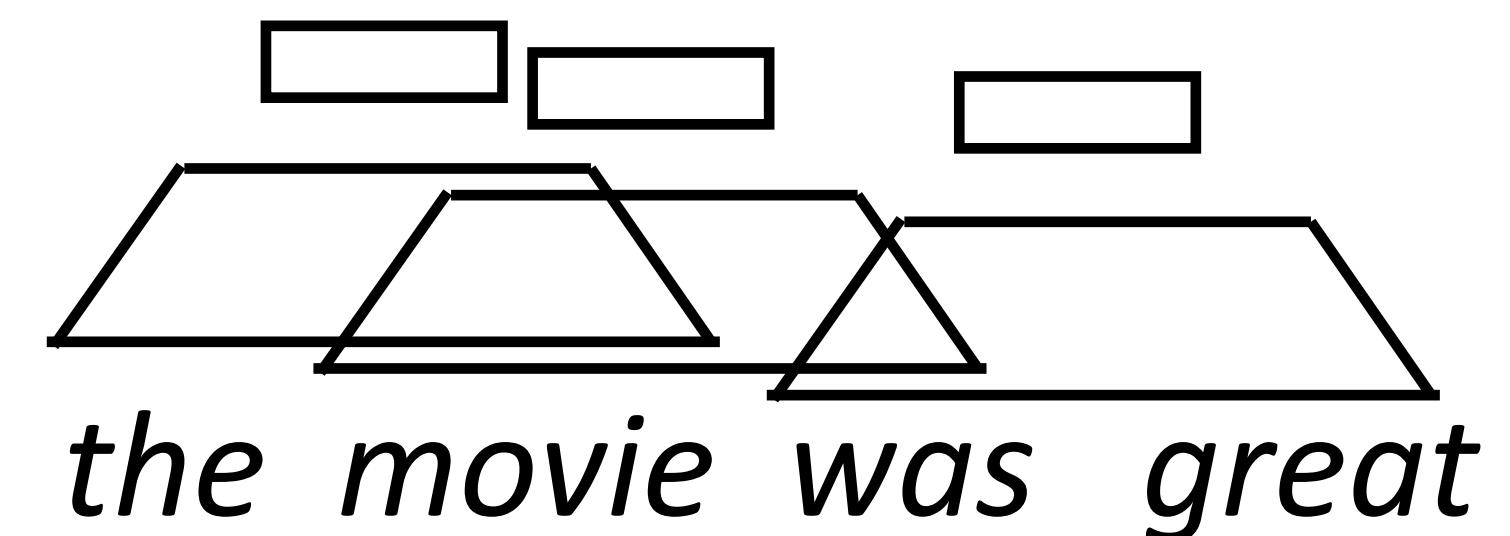
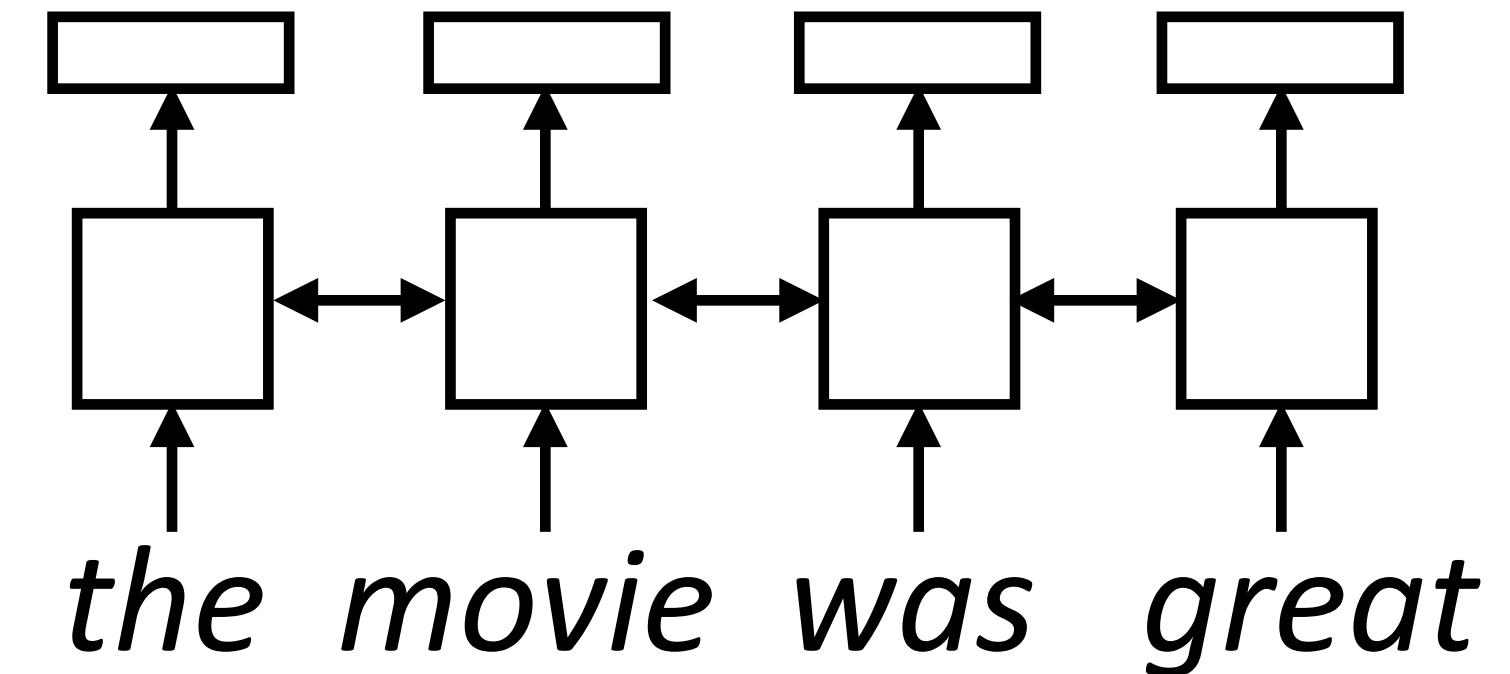
- ▶ There are a range of seq2seq modeling tasks we will address
- ▶ For more constrained problems: greedy/beam decoding are usually best
- ▶ For less constrained problems: nucleus sampling introduces favorable variation in the output



Transformers

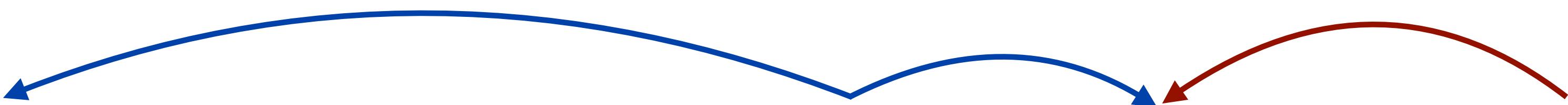
Sentence Encoders

- ▶ LSTM abstraction: maps each vector in a sentence to a new, context-aware vector
- ▶ CNNs do something similar with filters
- ▶ Attention can give us a third way to do this



Self-Attention

- ▶ Assume we're using GloVe — what do we want our neural network to do?



*The ballerina is very excited that **she** will dance in the **show**.*

- ▶ What words need to be contextualized here?
 - ▶ Pronouns need to look at antecedents
 - ▶ Ambiguous words should look at context
 - ▶ Words should look at syntactic parents/children
- ▶ Problem: LSTMs and CNNs don't do this

Self-Attention

- ▶ Want:

The diagram illustrates the concept of self-attention. It shows a sentence: "The ballerina is very excited that **she** will dance in the **show**". Blue curved arrows originate from the word "she" and point back to the words "the" and "show". A red curved arrow originates from the word "show" and points back to itself. This visualizes how each word's embedding is updated based on the context of other words in the sequence.

*The ballerina is very excited that **she** will dance in the **show**.*

- ▶ LSTMs/CNNs: tend to look at local context

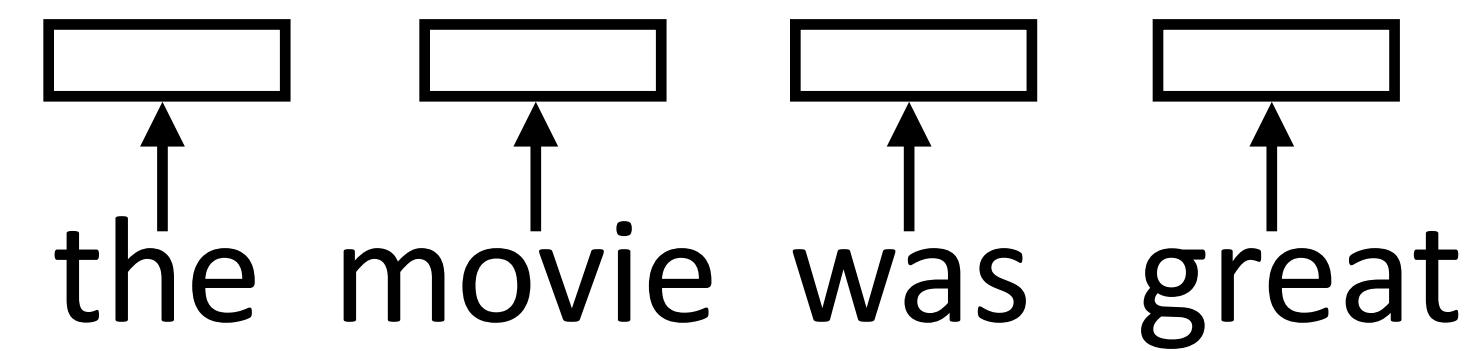
The diagram illustrates the concept of local context attention. It shows the same sentence: "The ballerina is very excited that **she** will dance in the **show**". In this version, multiple blue curved arrows originate from the word "she" and point to its immediate neighbors: "the", "will", and "dance". A single red curved arrow originates from the word "show" and points to itself. This highlights that traditional sequence models like LSTMs and CNNs focus primarily on nearby words rather than capturing long-range dependencies.

*The ballerina is very excited that **she** will dance in the **show**.*

- ▶ To appropriately contextualize embeddings, we need to pass information over long distances dynamically for each word

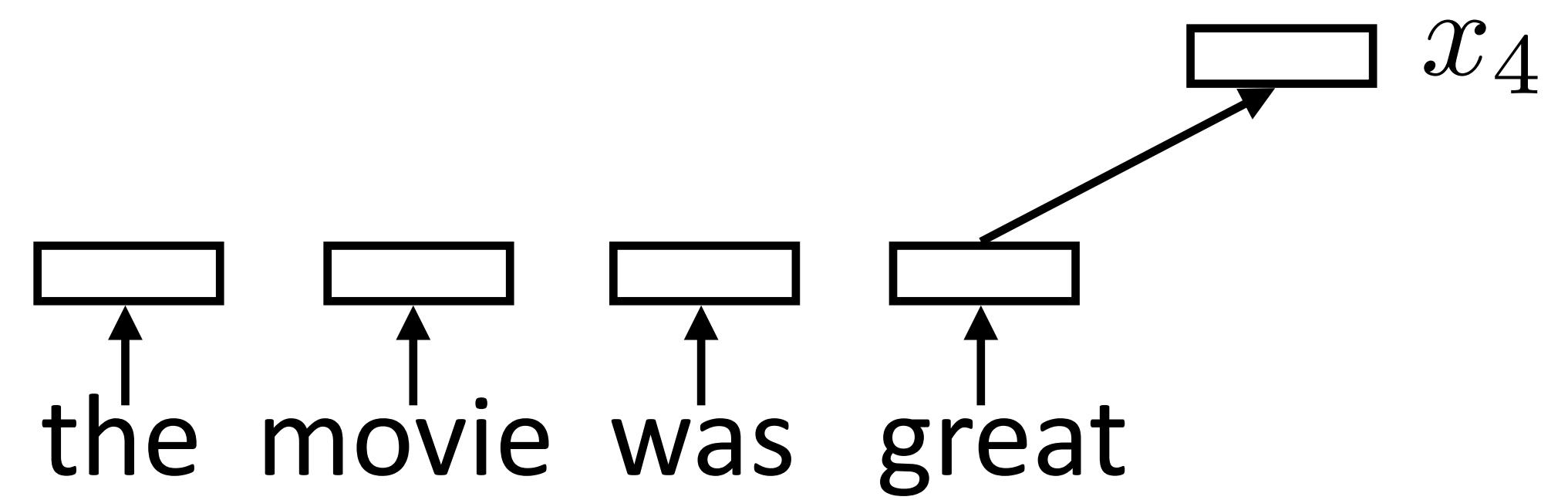
Self-Attention

- ▶ Each word forms a “query” which then computes attention over each word



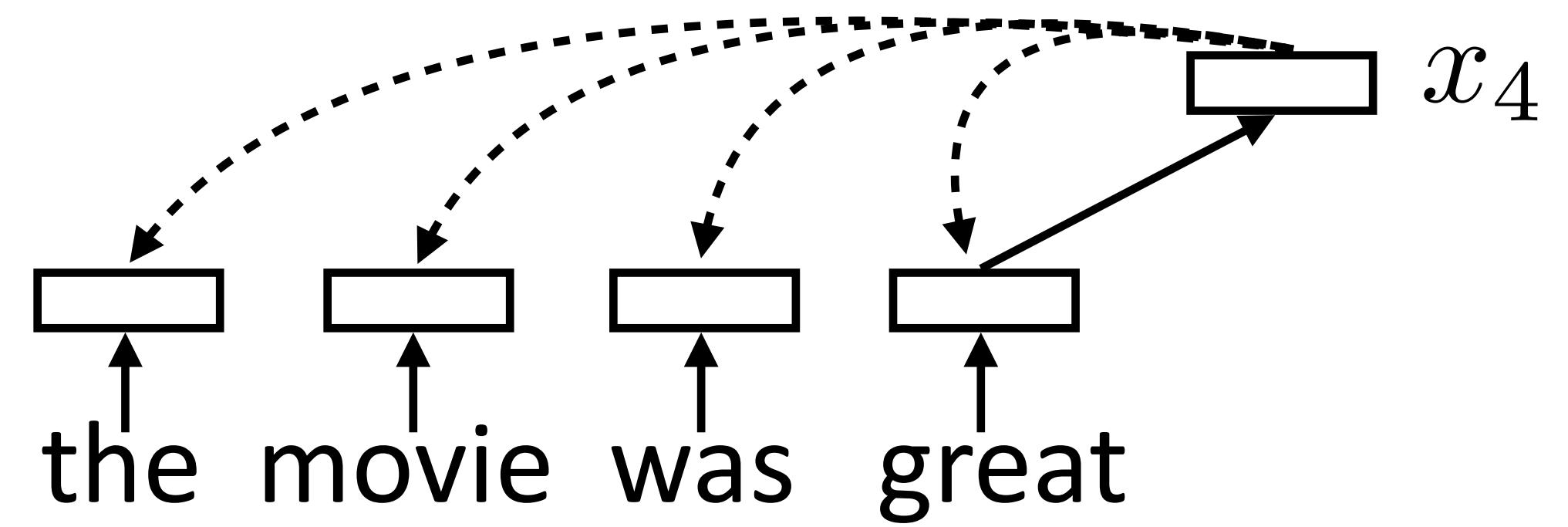
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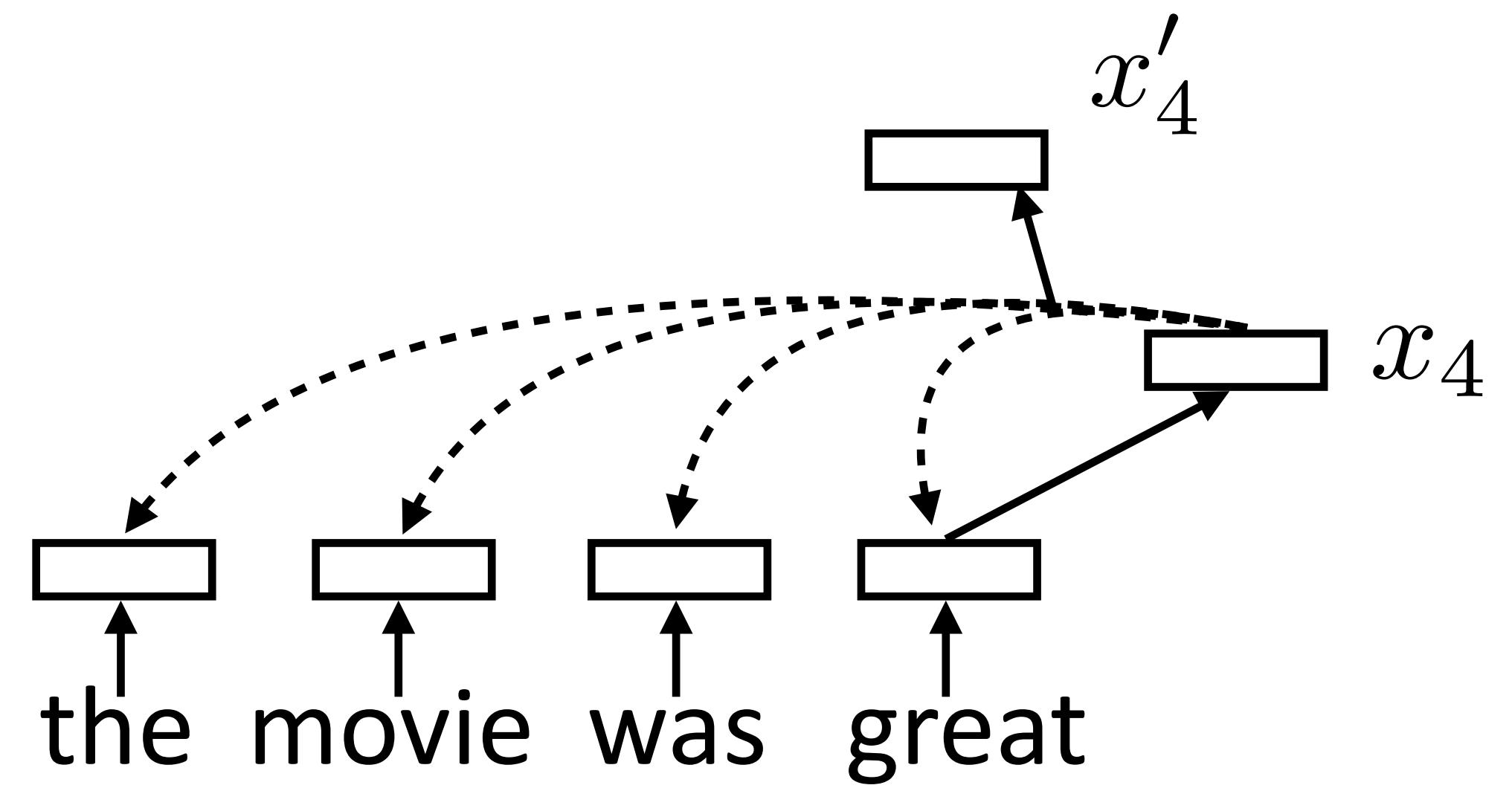
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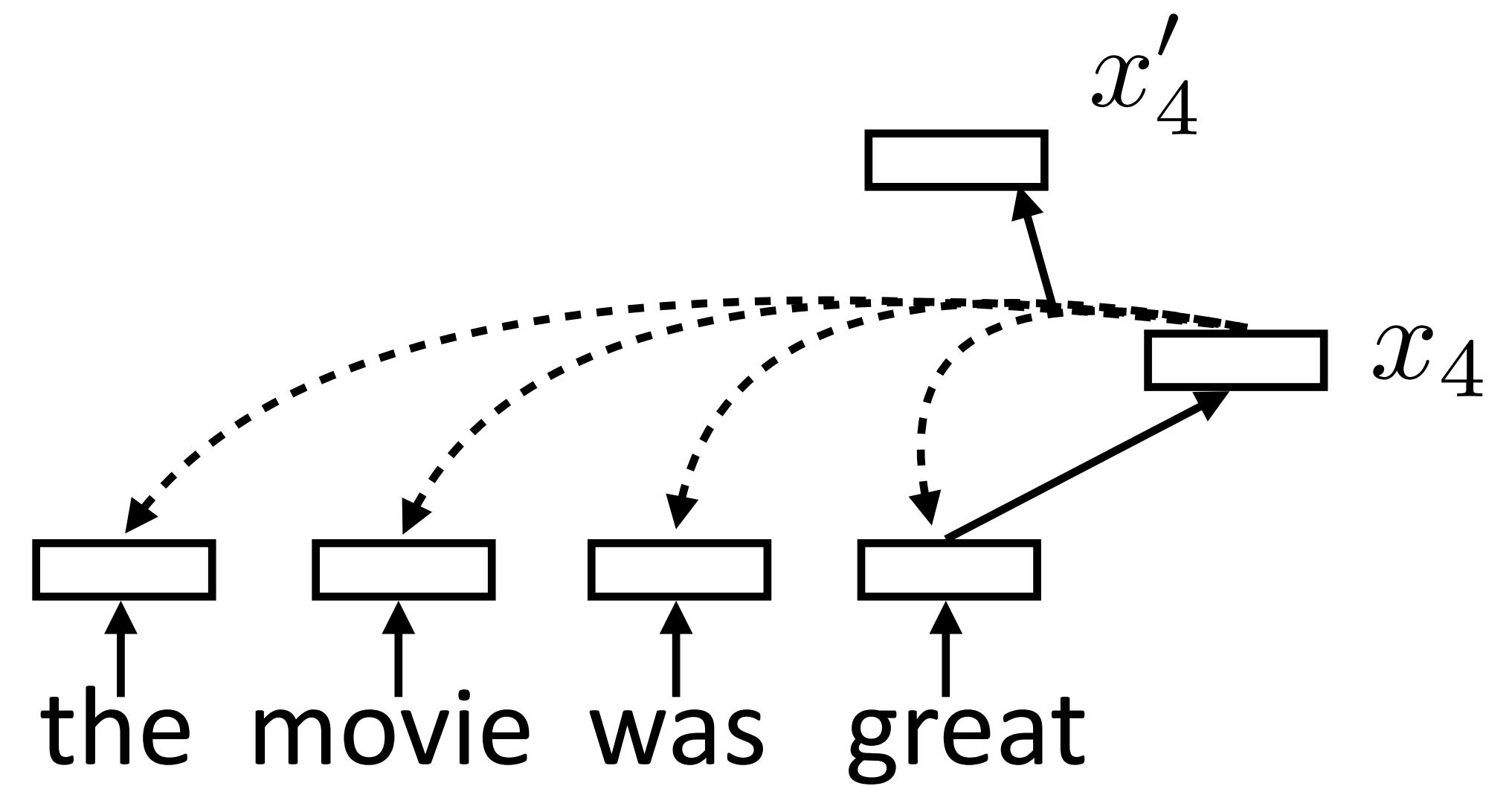
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$$\alpha_{i,j} = \text{softmax}(x_i^\top x_j) \text{ scalar}$$

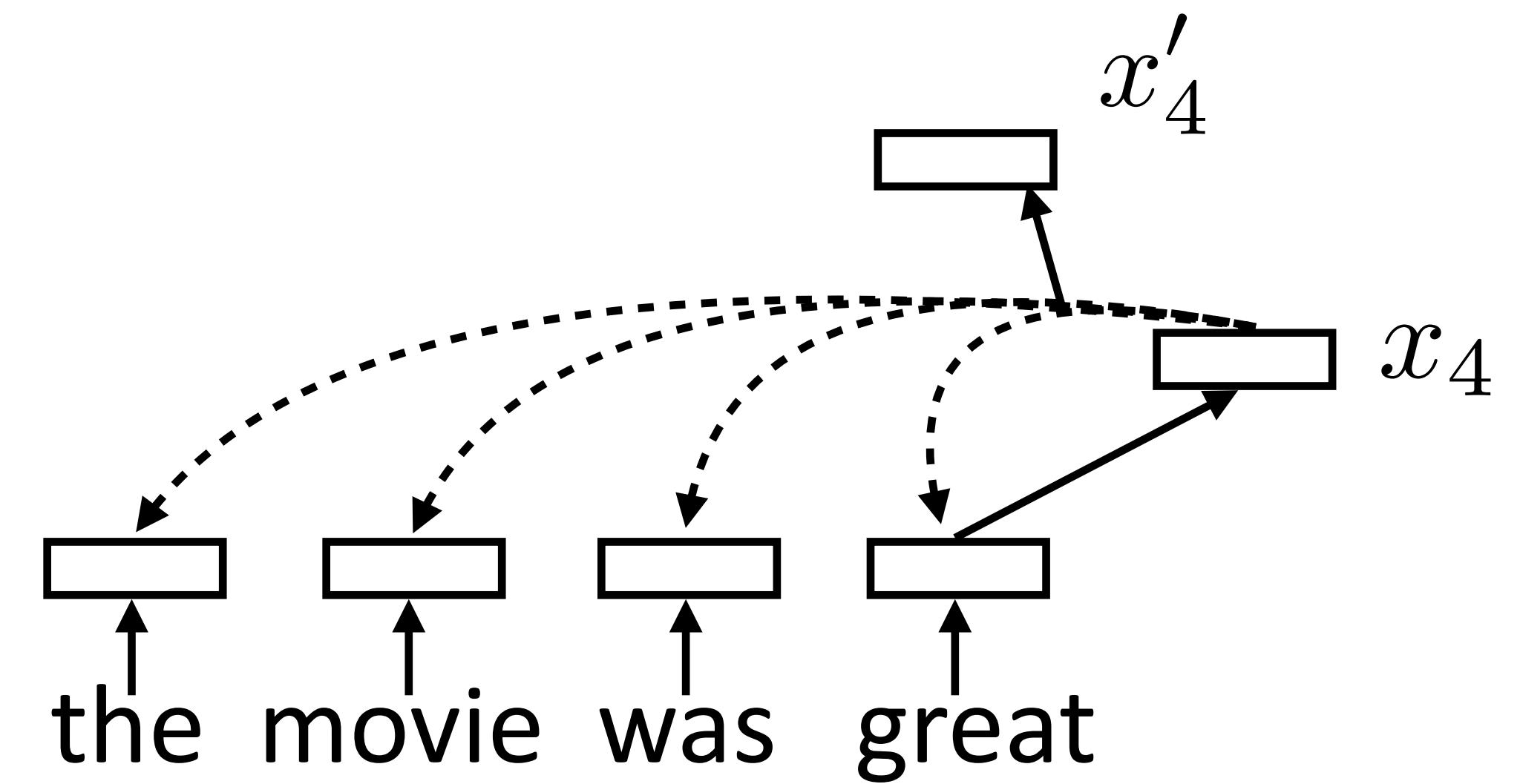


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$$\alpha_{i,j} = \text{softmax}(x_i^\top x_j) \quad \text{scalar}$$

$$x'_i = \sum_{j=1}^n \alpha_{i,j} x_j \quad \text{vector} = \text{sum of scalar * vector}$$

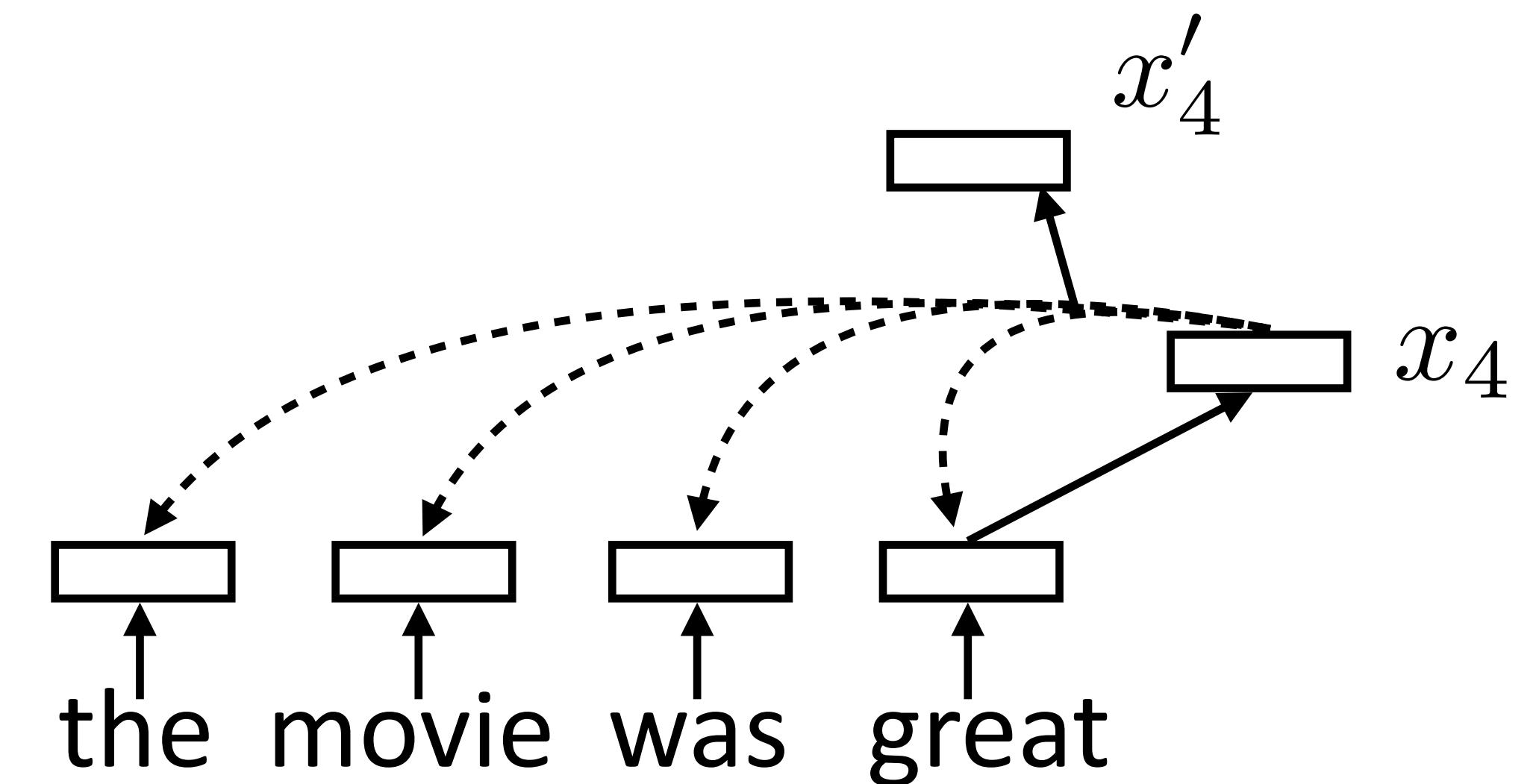


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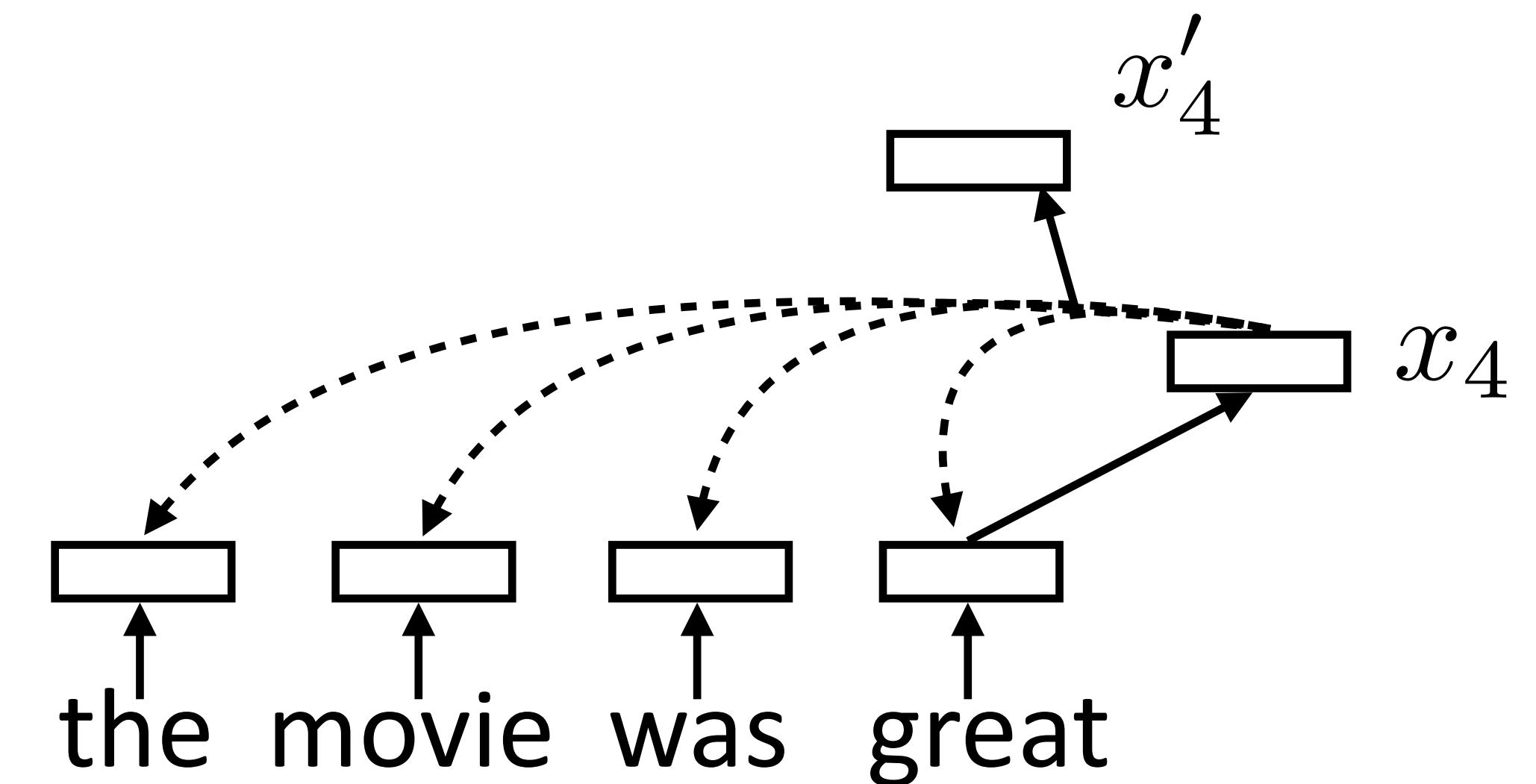
- ▶ Multiple “heads” analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

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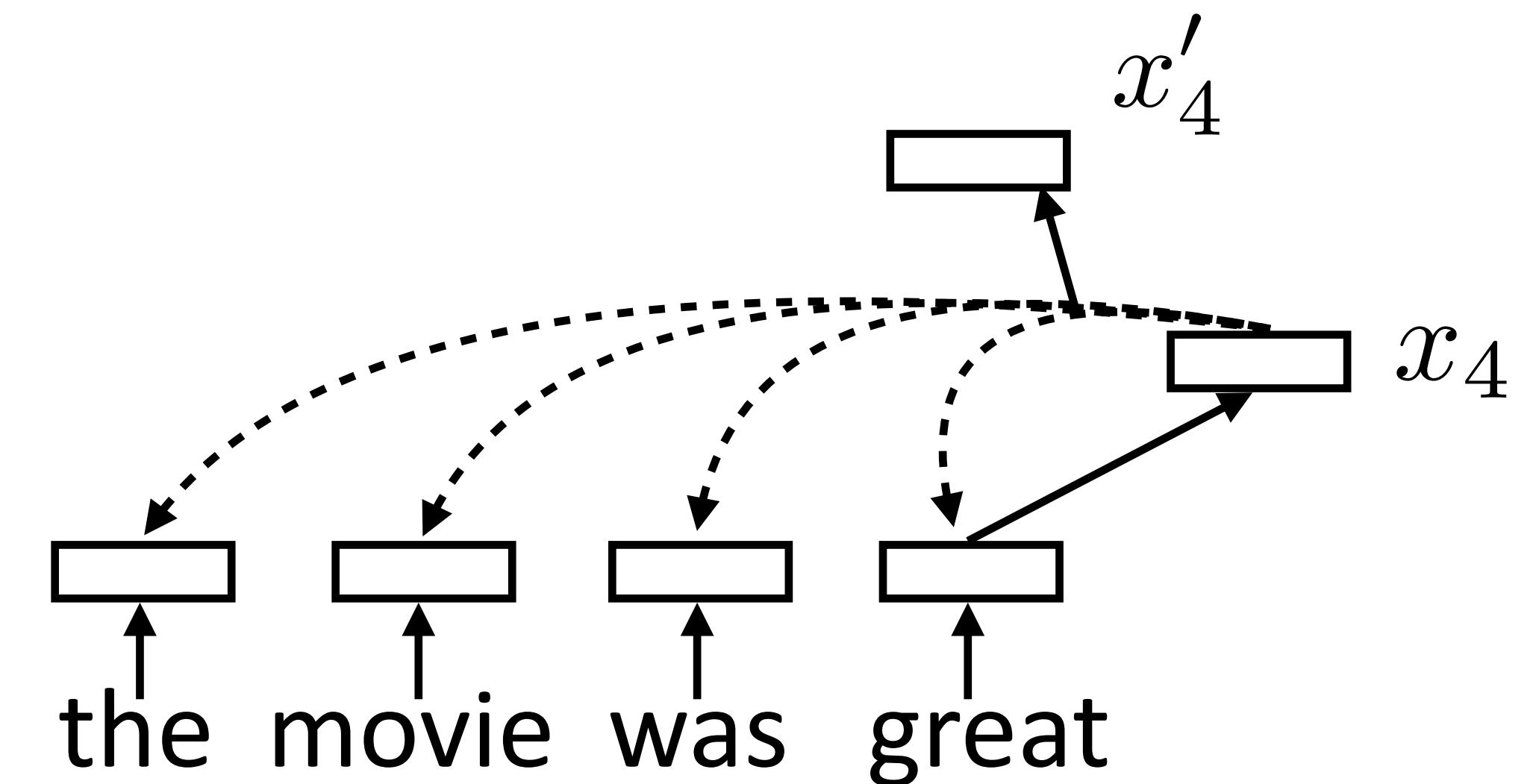
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- ▶ Multiple “heads” analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

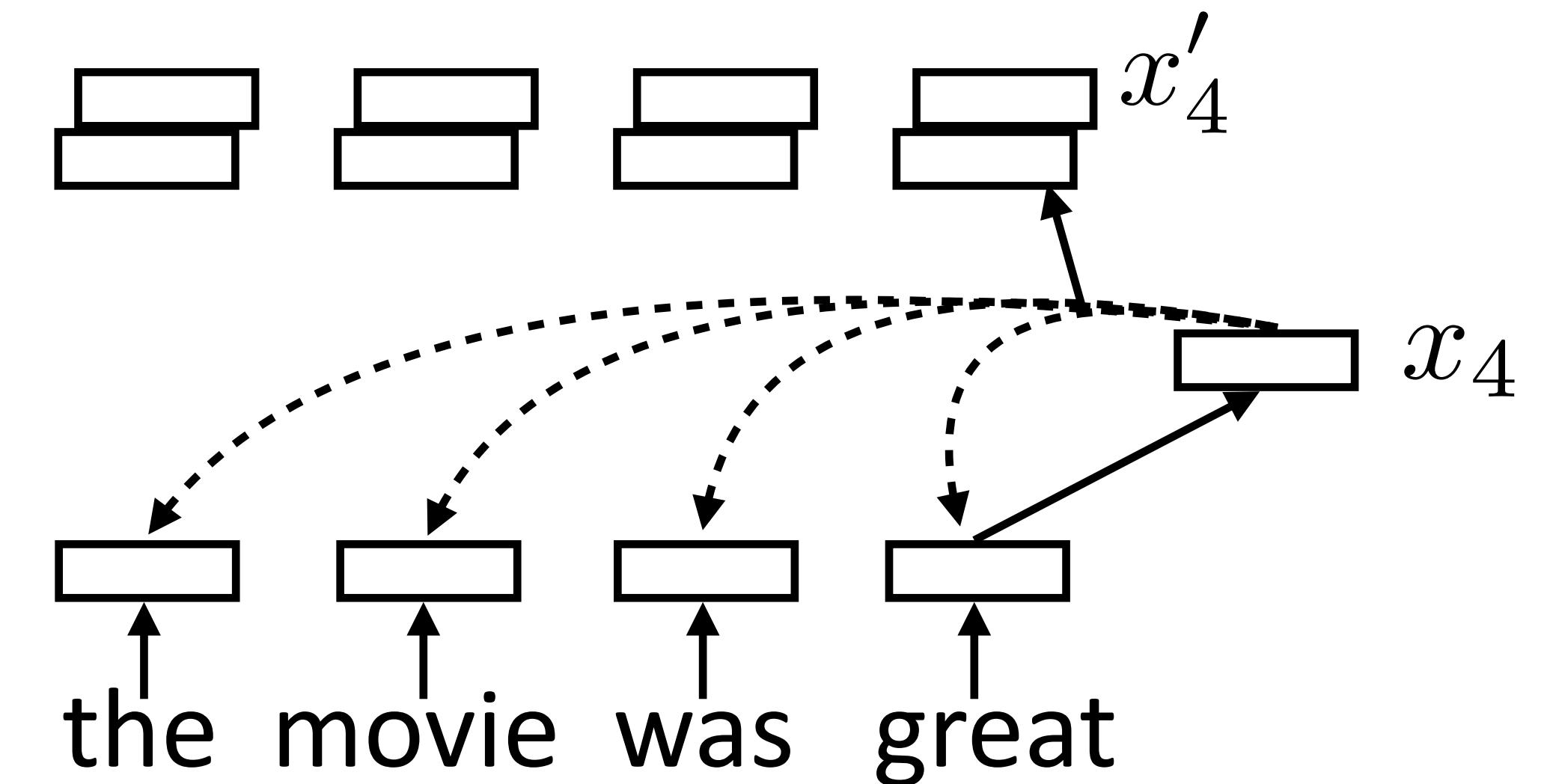
$$\alpha_{k,i,j} = \text{softmax}(x_i^\top W_k x_j) \quad x'_{k,i} = \sum_{j=1}^n \alpha_{k,i,j} V_k x_j$$

Self-Attention

- ▶ Each word forms a “query” which then computes attention over each word

$$\alpha_{i,j} = \text{softmax}(x_i^\top x_j) \quad \text{scalar}$$

$$x'_i = \sum_{j=1}^n \alpha_{i,j} x_j \quad \text{vector} = \text{sum of scalar * vector}$$



- ▶ Multiple “heads” analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

$$\alpha_{k,i,j} = \text{softmax}(x_i^\top W_k x_j) \quad x'_{k,i} = \sum_{j=1}^n \alpha_{k,i,j} V_k x_j$$

What can self-attention do?

*The ballerina is very excited that **she** will dance in the **show**.*

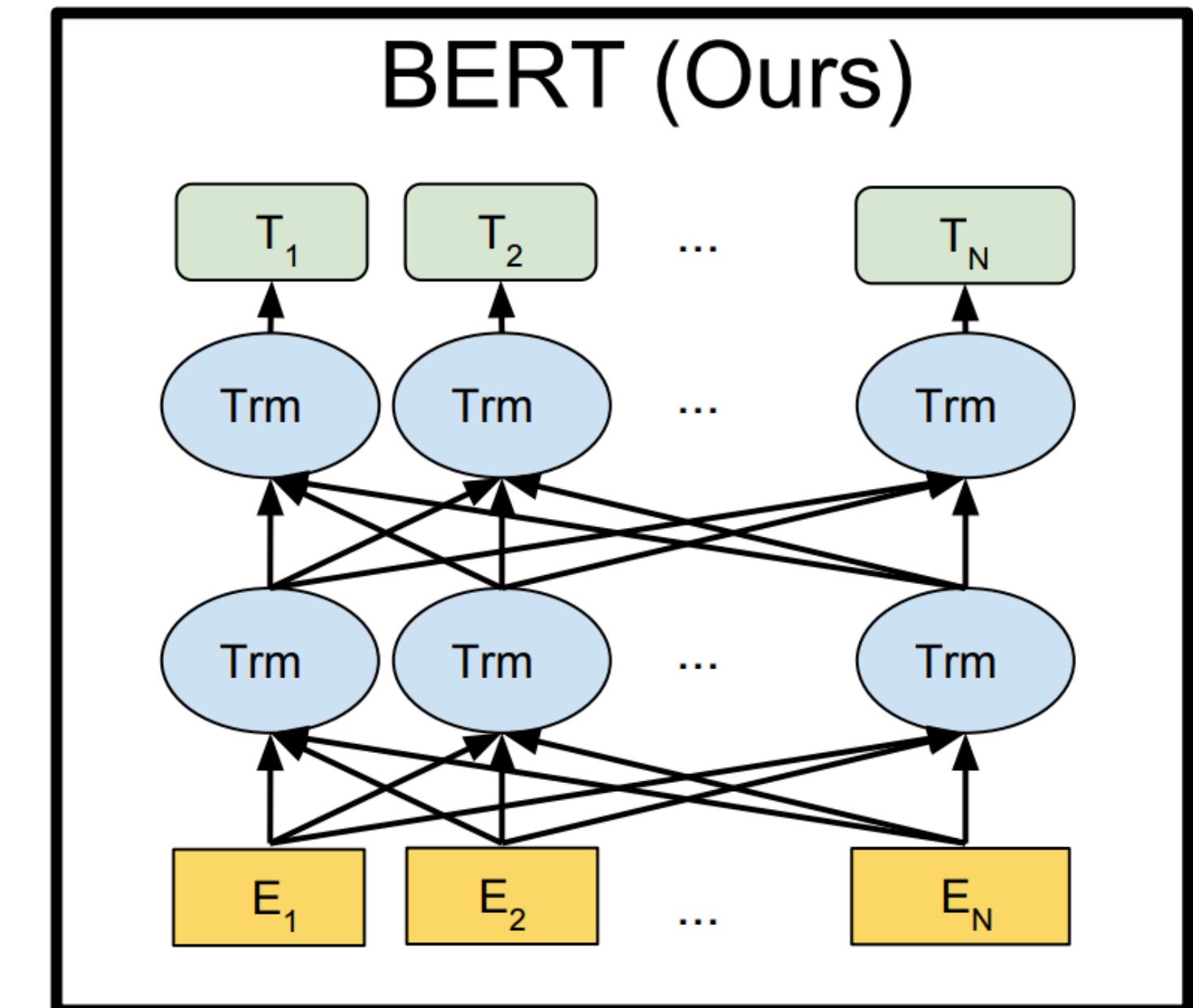
0	0.5	0	0	0.1	0.1	0	0.1	0.2	0	0	0
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0	0.1	0	0	0	0	0	0	0.5	0	0.4	0
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- ▶ Attend nearby + to semantically related terms
- ▶ This is a demonstration, we will revisit what these models actually learn when we discuss BERT
- ▶ Why multiple heads? Softmaxes end up being peaked, single distribution cannot easily put weight on multiple things

Transformer Uses

- ▶ Supervised: transformer can replace LSTM as encoder, decoder, or both; will revisit this when we discuss MT
- ▶ Unsupervised: transformers work better than LSTM for unsupervised pre-training of embeddings: predict word given context words
- ▶ BERT (Bidirectional Encoder Representations from Transformers): pretraining transformer language models similar to ELMo
- ▶ Stronger than similar methods, SOTA on ~11 tasks (including NER — 92.8 F1)



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- ▶ Used for tasks including summarization and sentence ordering
- ▶ Explicitly copying input can be beneficial as well
- ▶ Transformers are strong models we'll come back to later