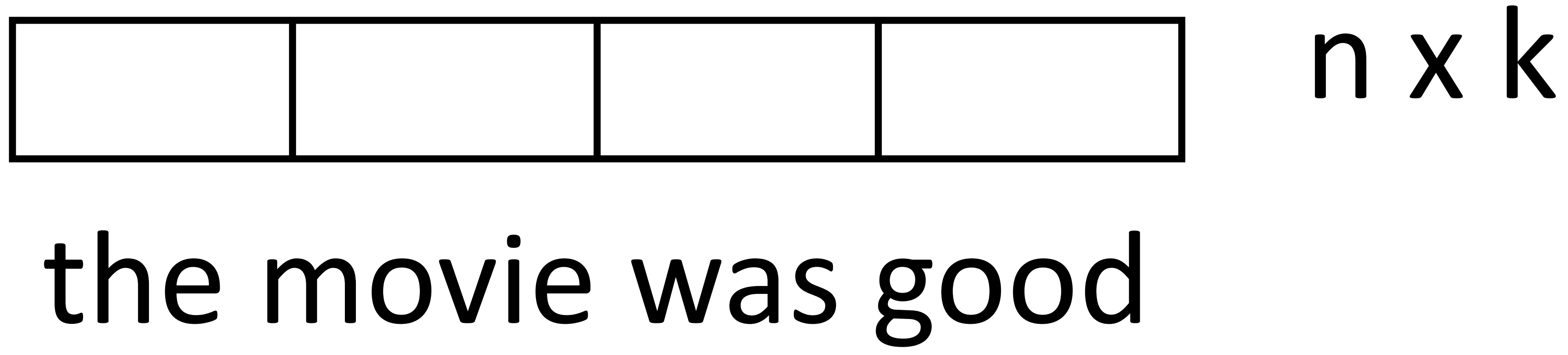
Lecture 11: Seq2Seq + Attention

Alan Ritter

(many slides from Greg Durrett)

Recall: CNNs vs. LSTMs



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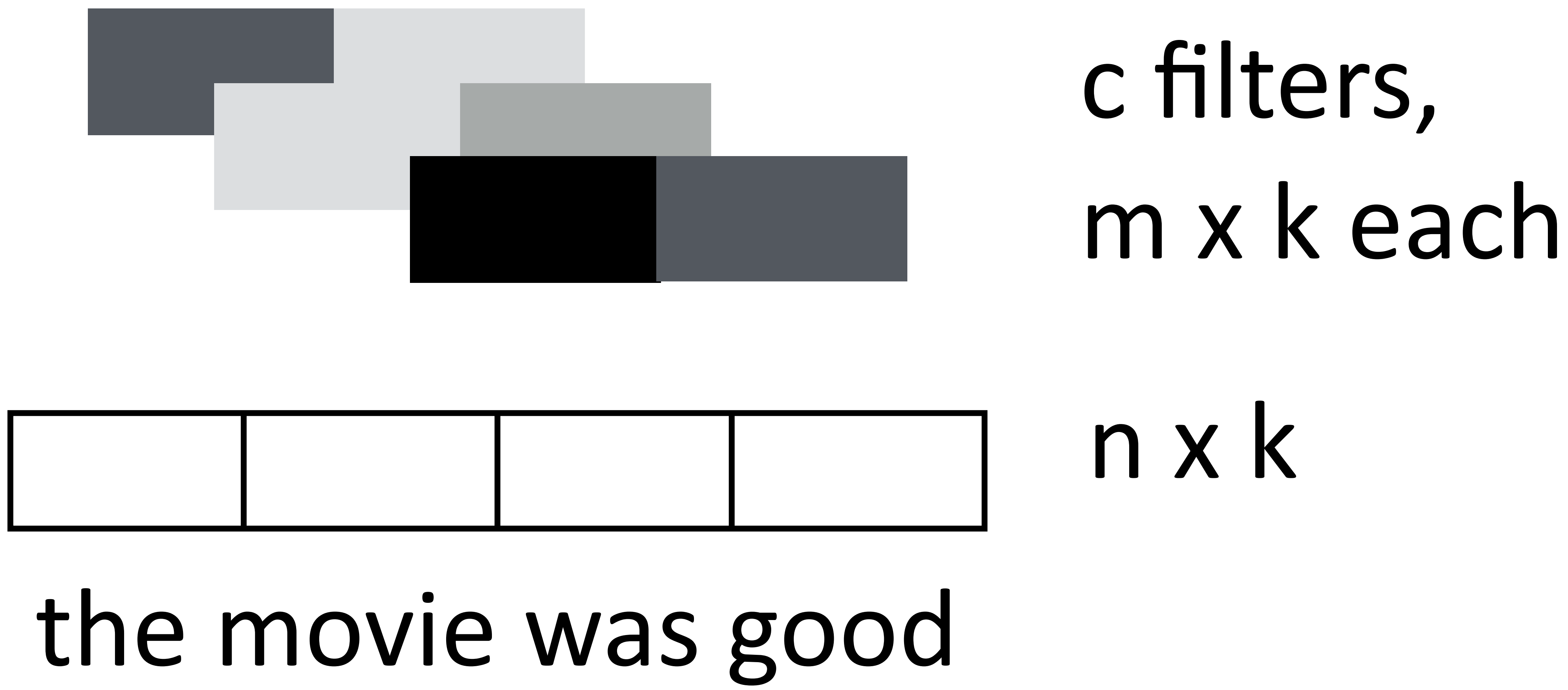

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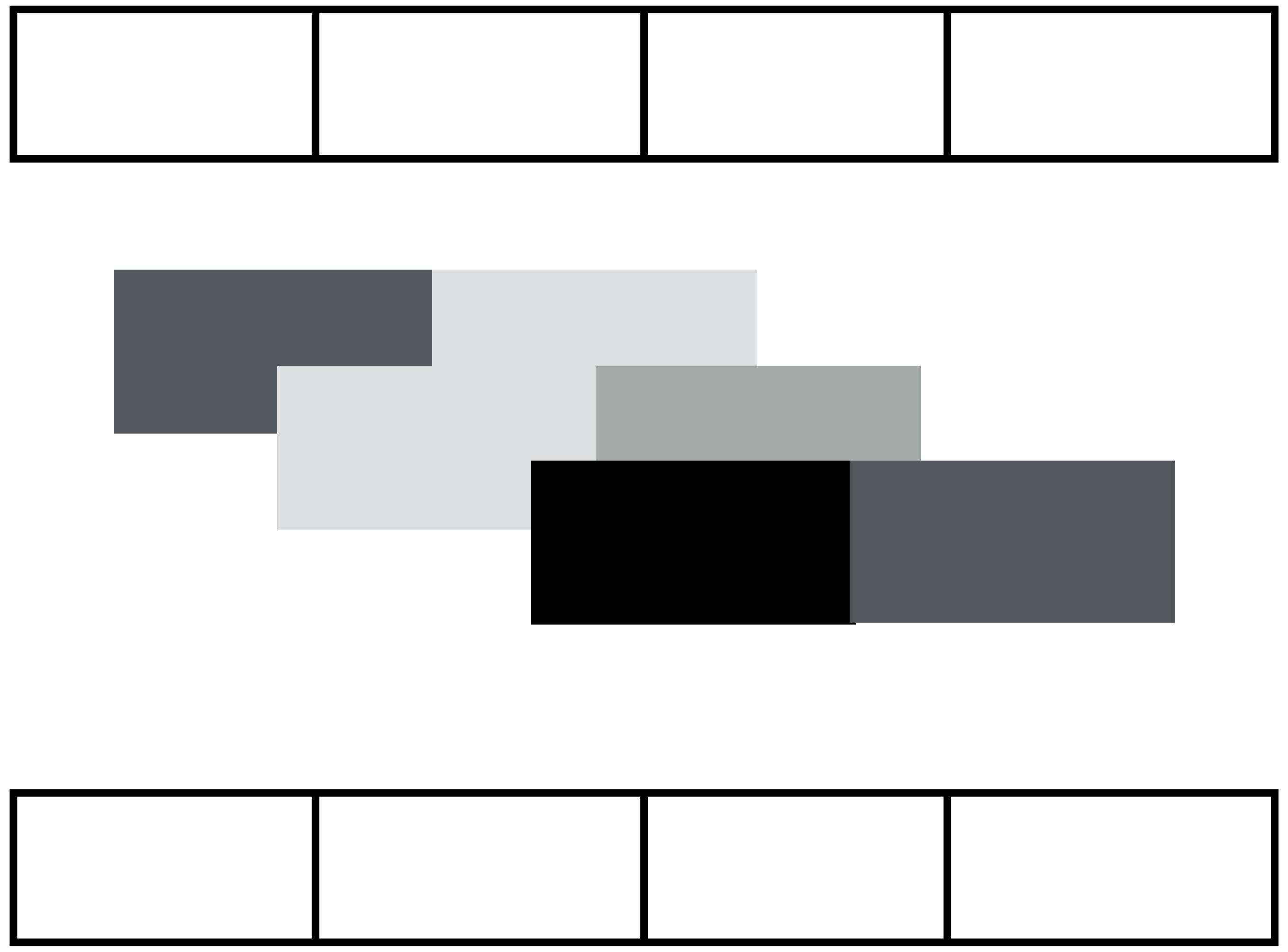


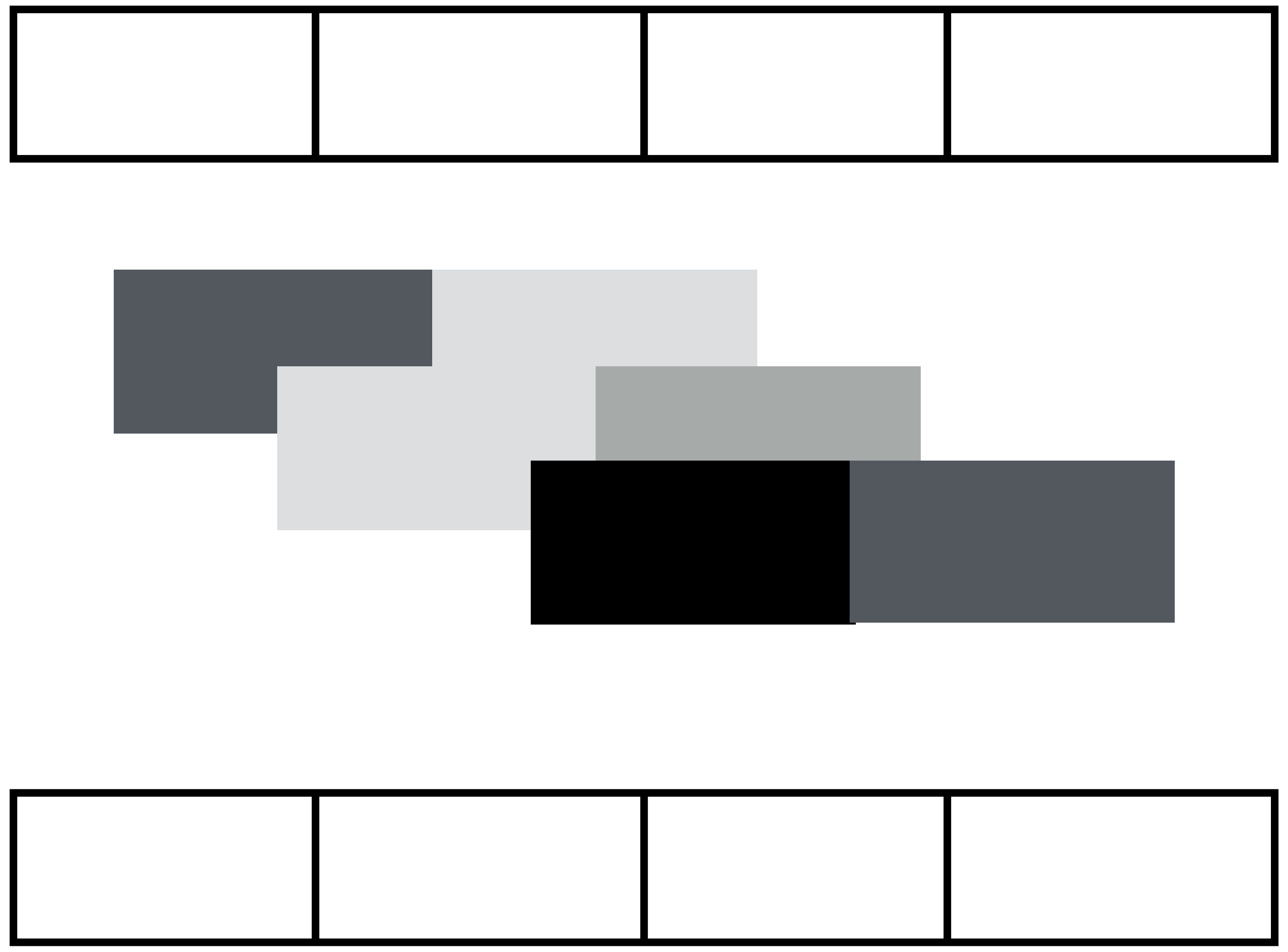
O(n) x c

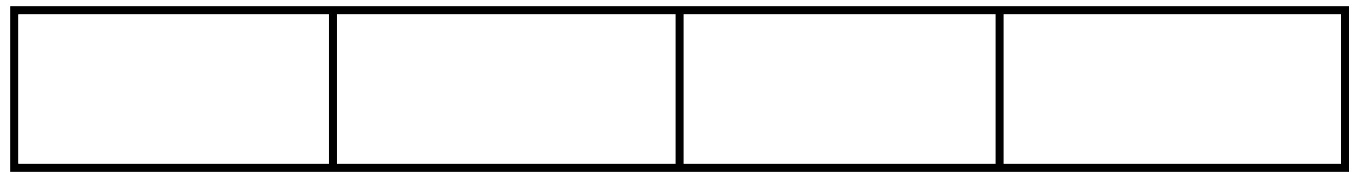
c filters,
m x k each

n x k

the movie was good

Recall: CNNs vs. LSTMs





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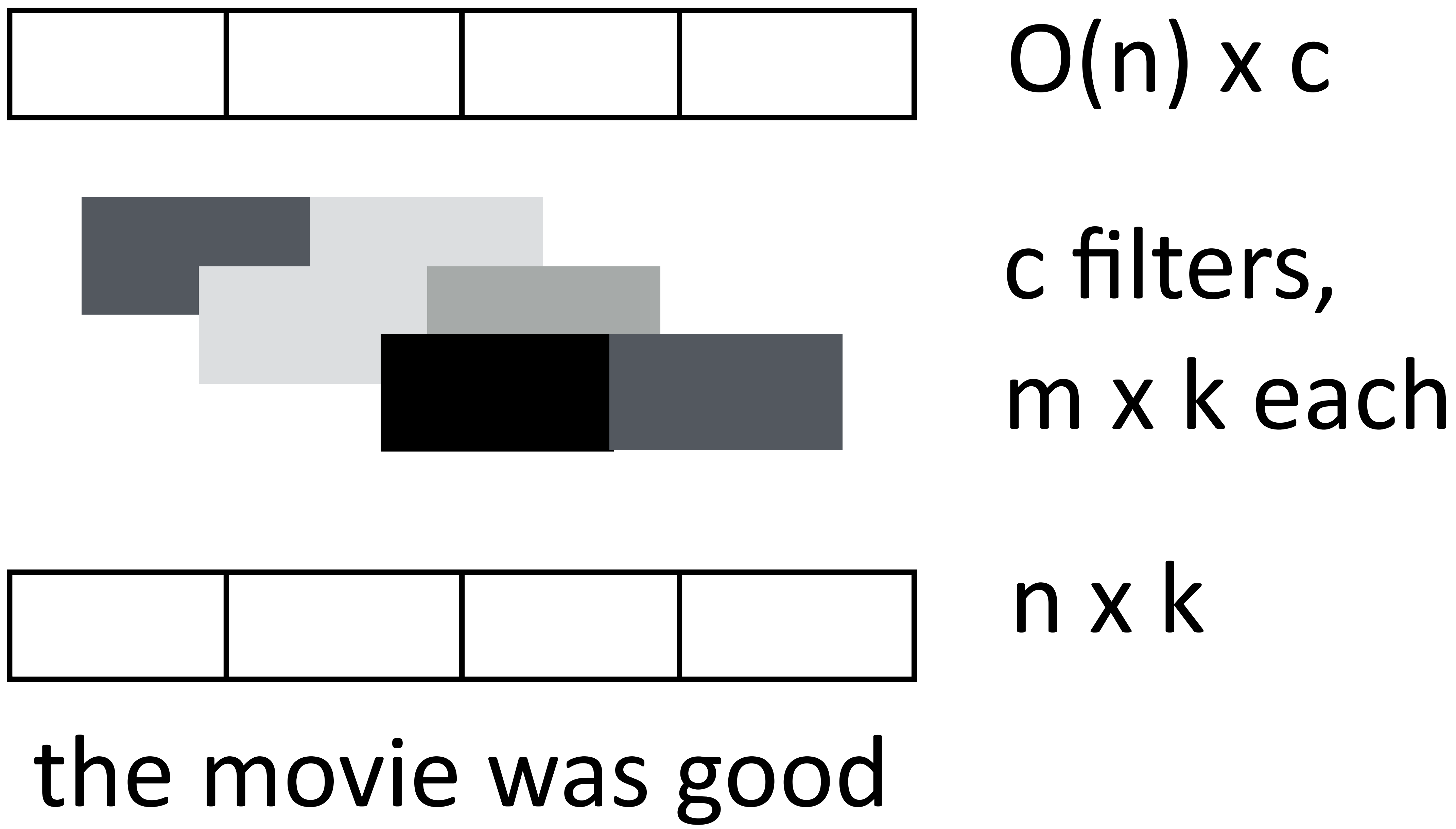

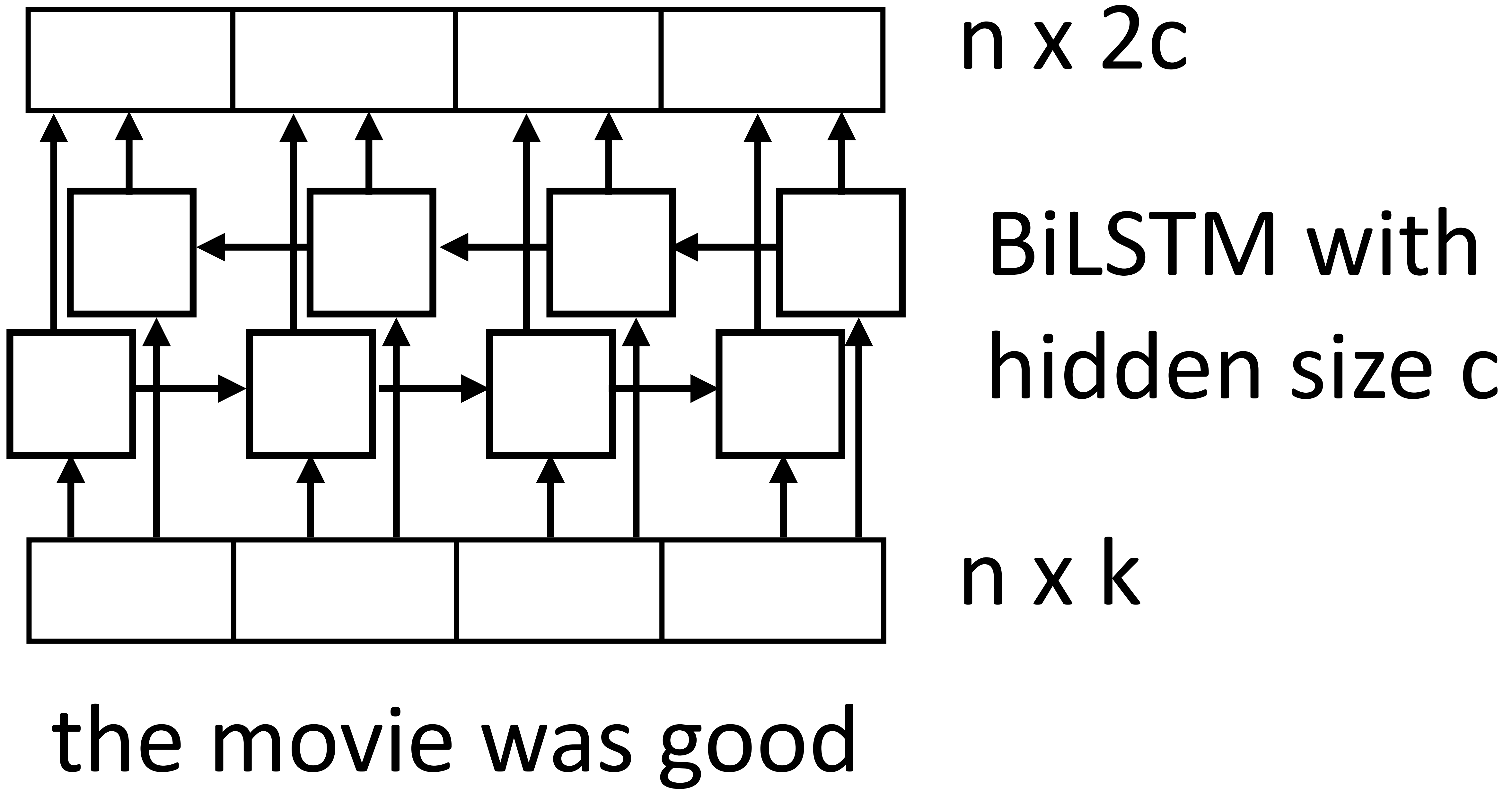

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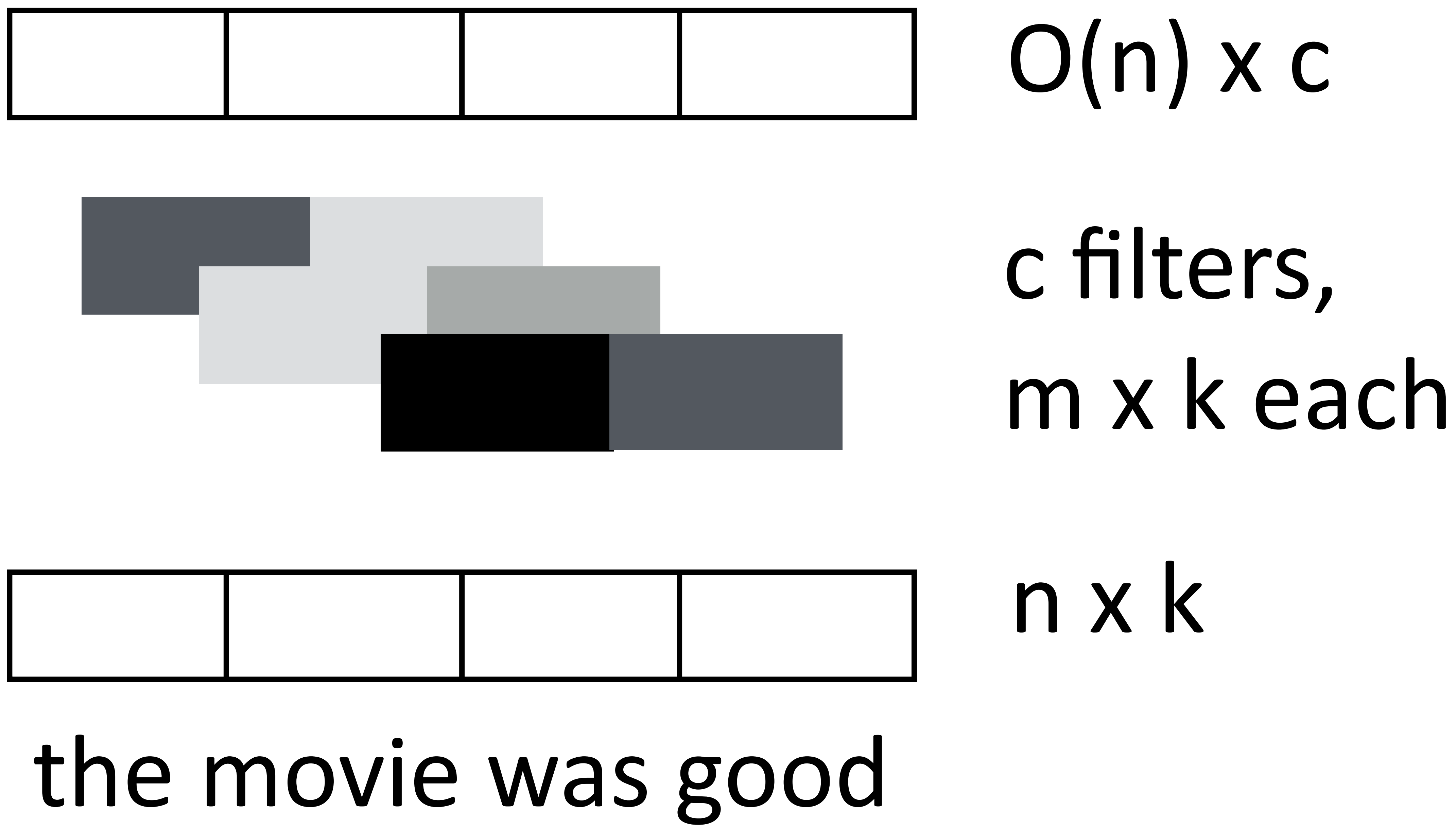
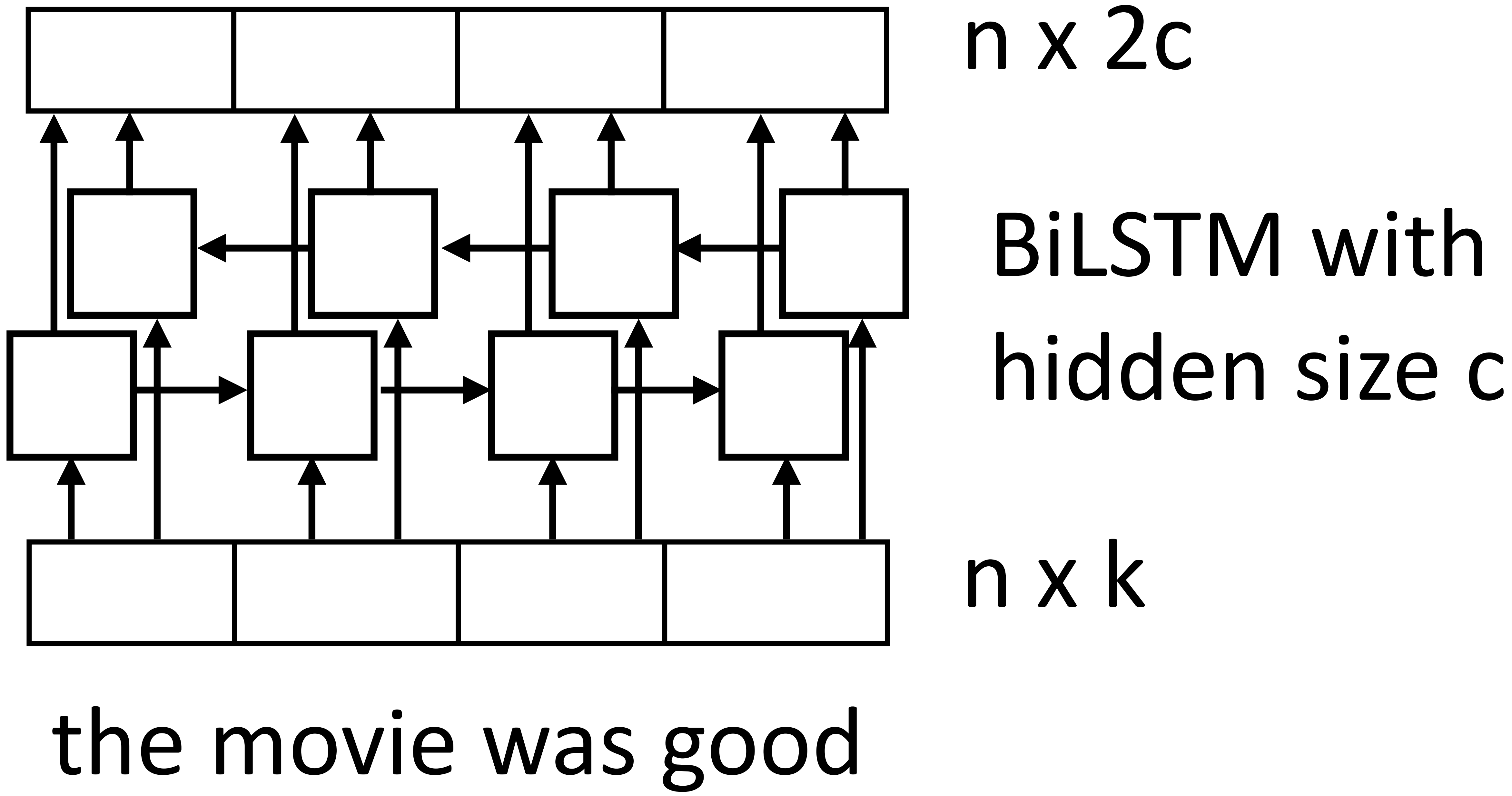
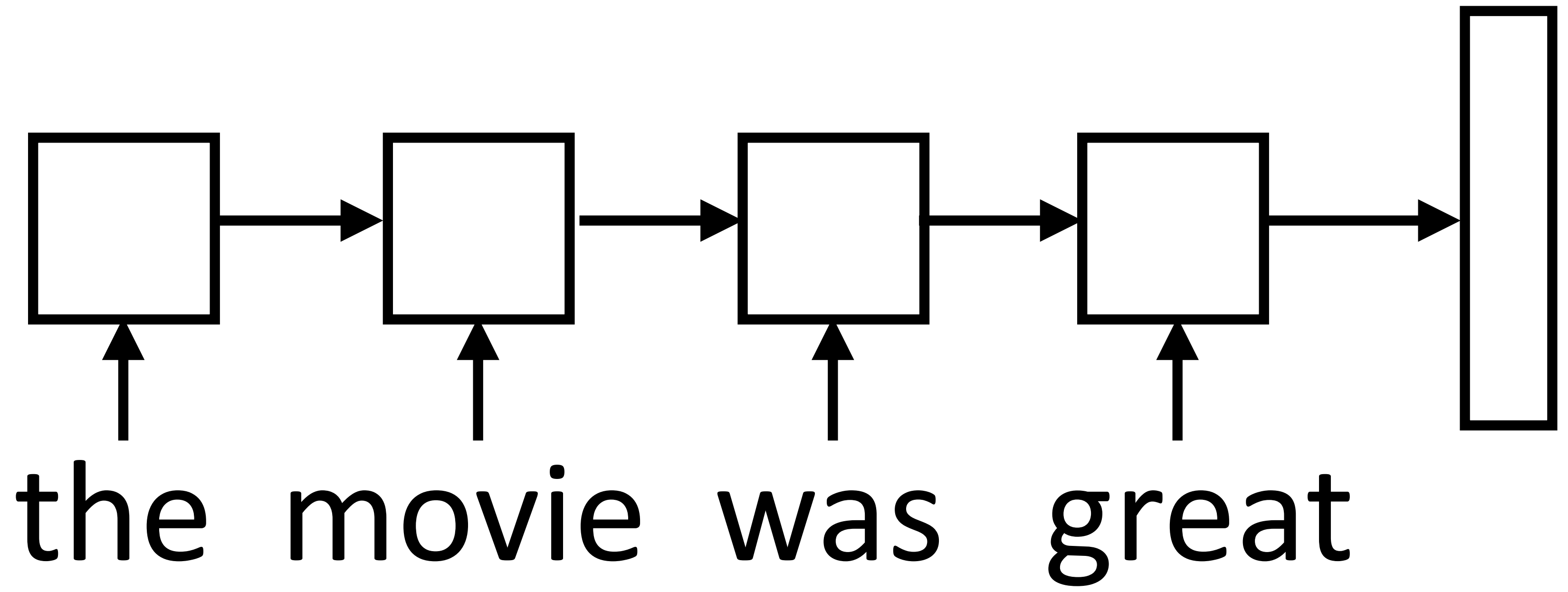




- Both LSTMs and convolutional layers transform the input using context
- LSTM: “globally” looks at the entire sentence (but local for many problems)
- CNN: local depending on filter width + number of layers

Encoder-Decoder

- Encode a sequence into a fixed-sized vector



Sutskever et al. (2014)

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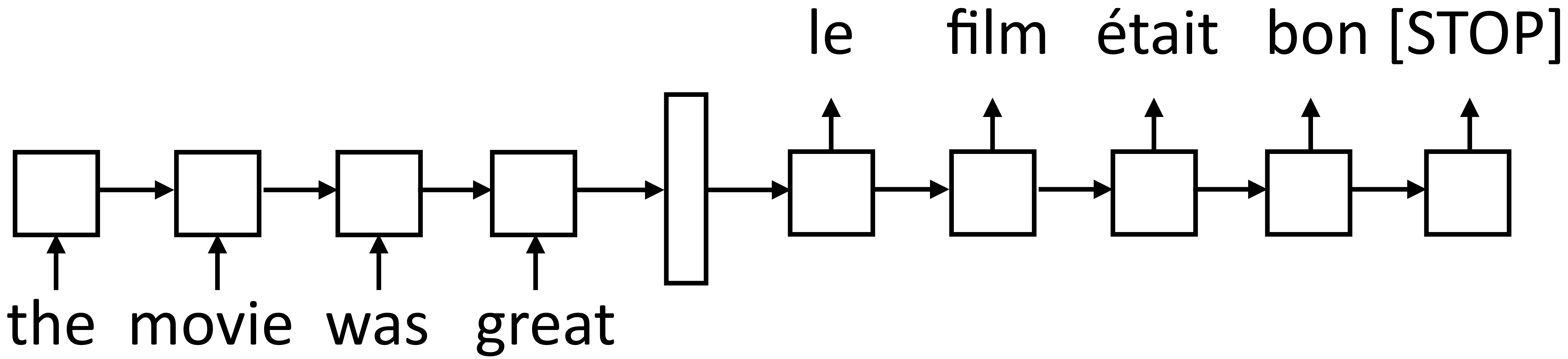

- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

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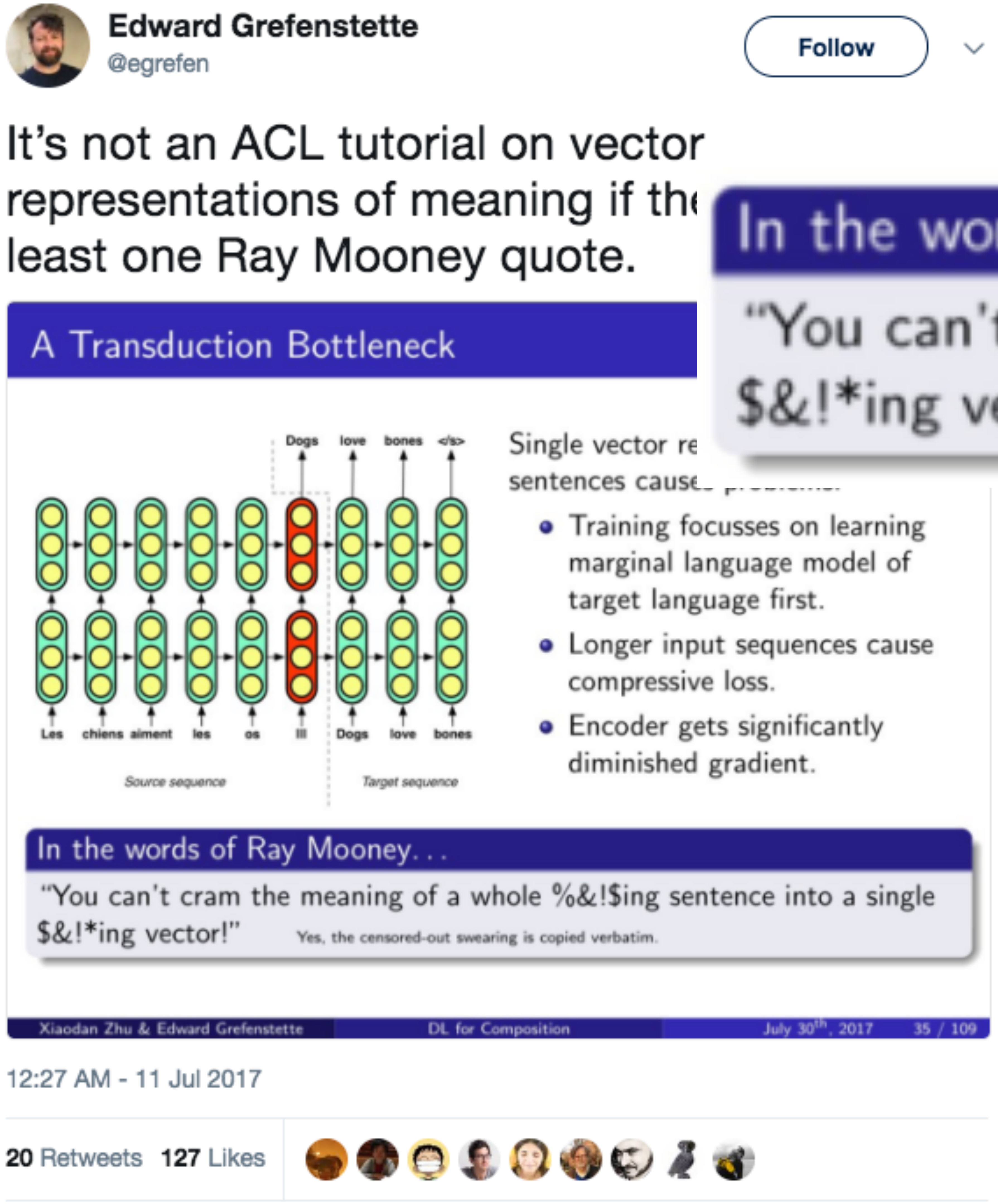
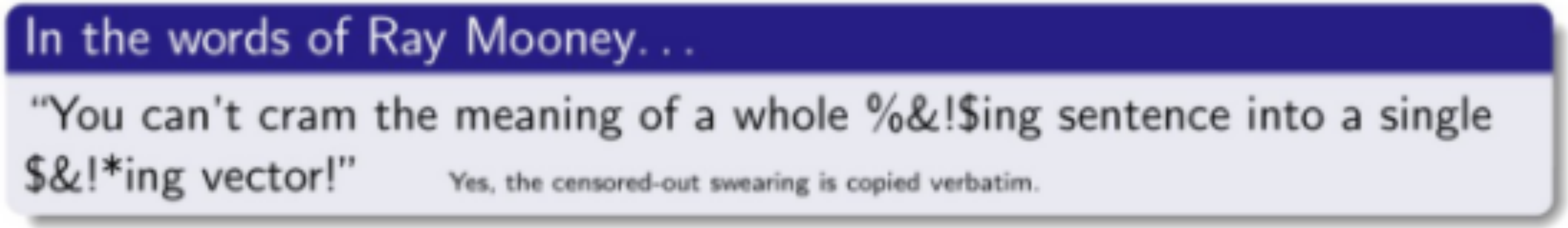
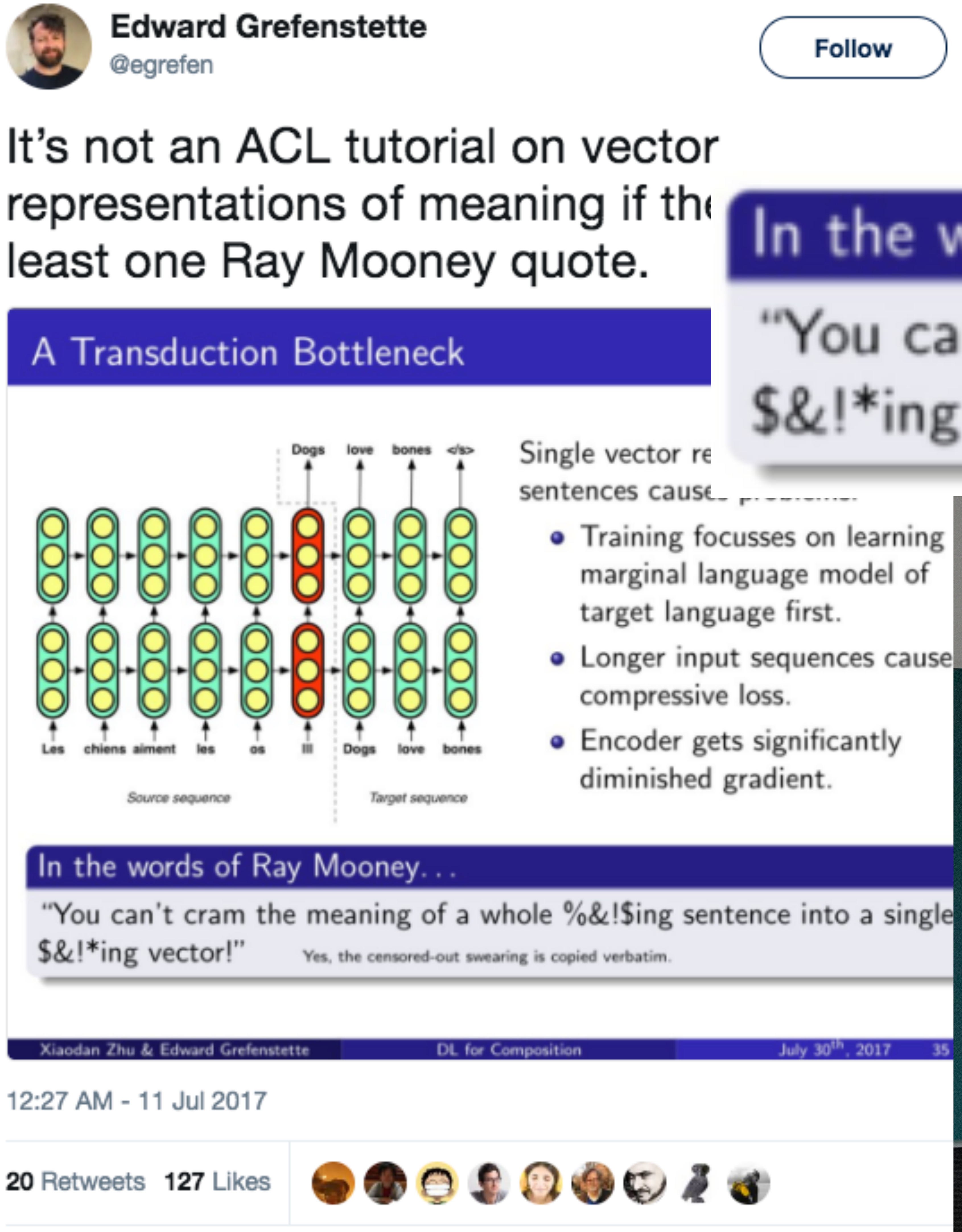
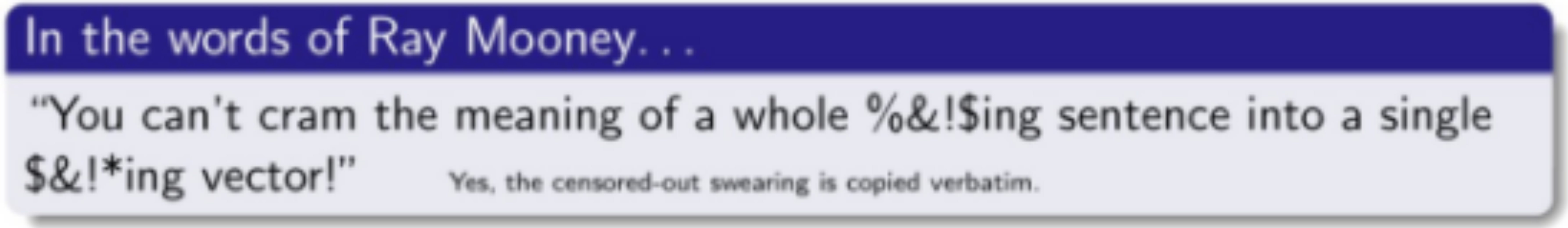


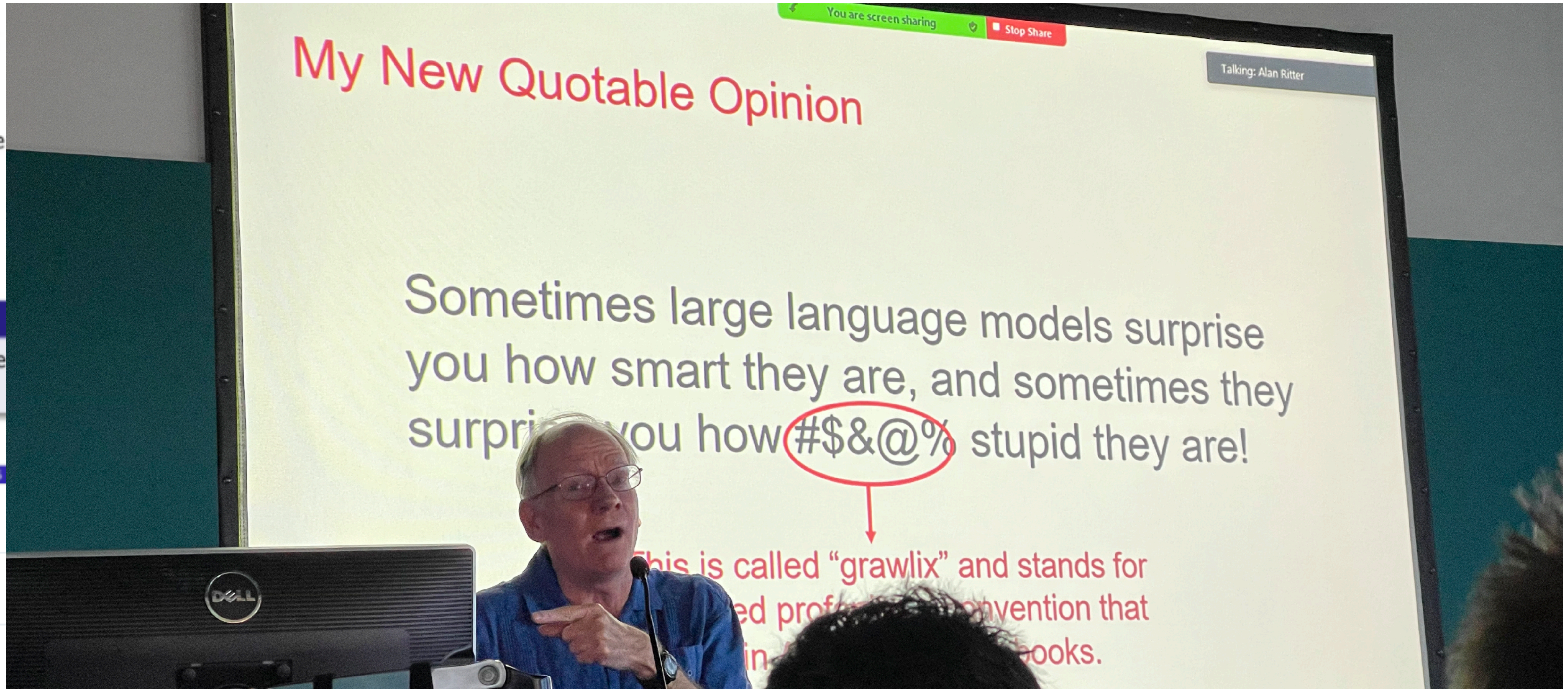


- Is this true? Sort of…we'll come back to this later

Encoder-Decoder







Model

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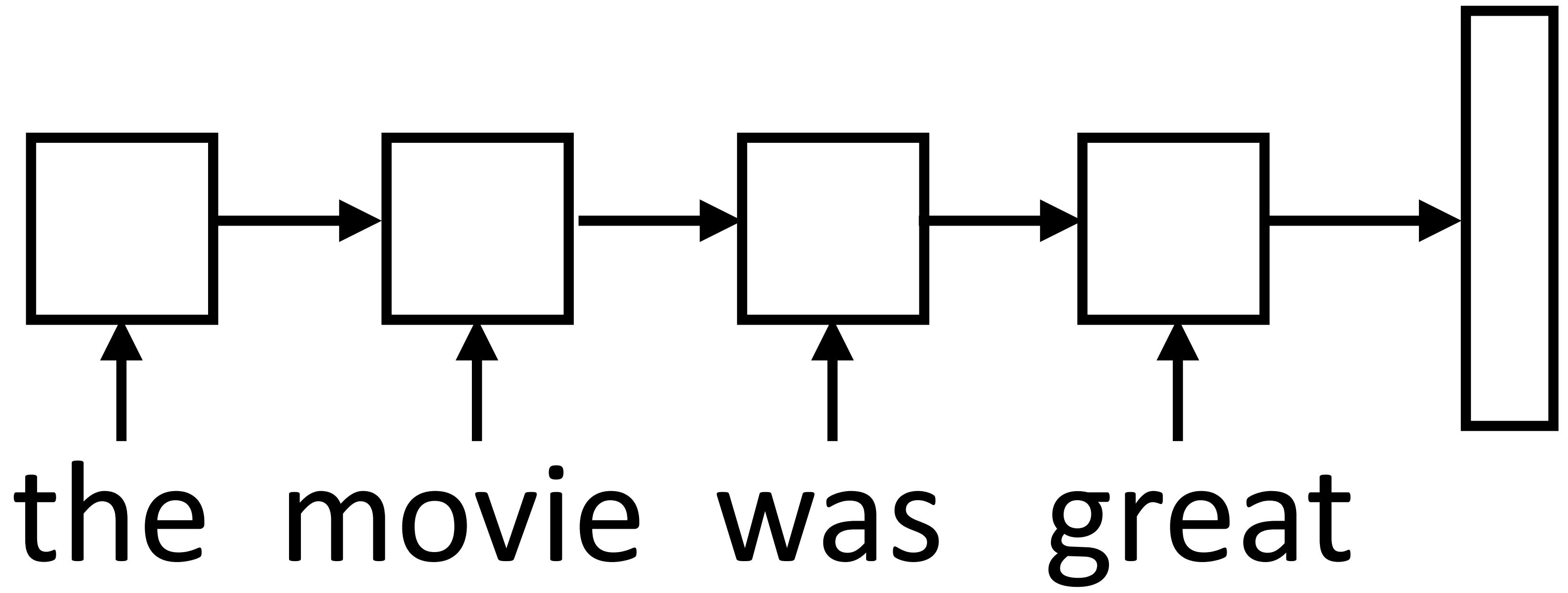

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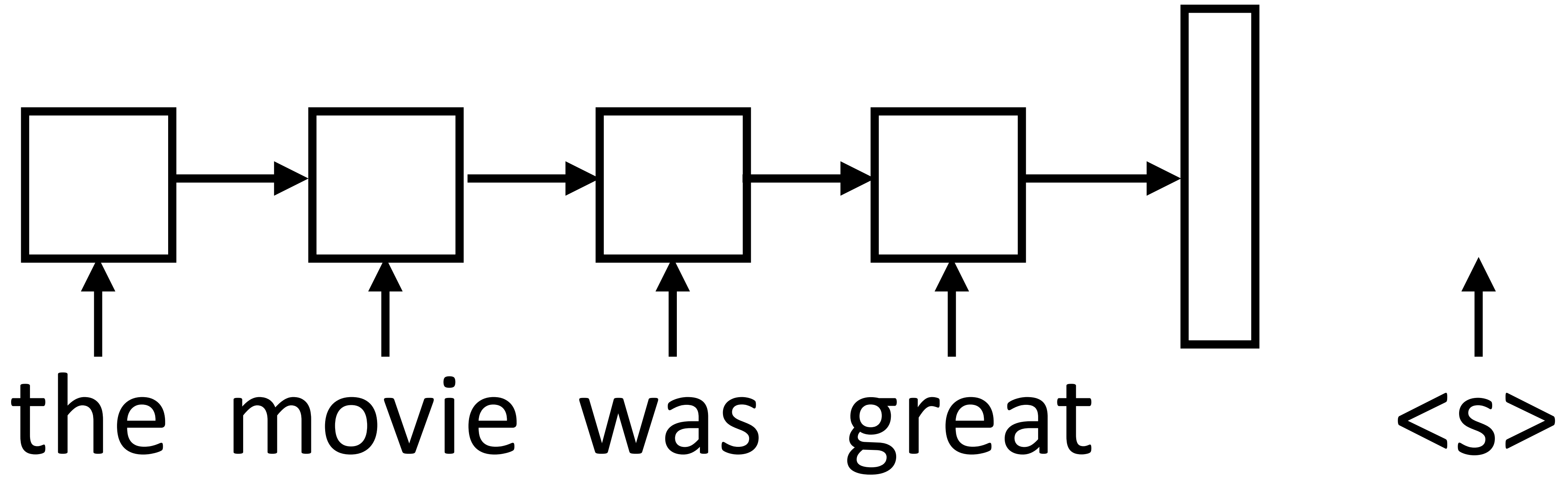

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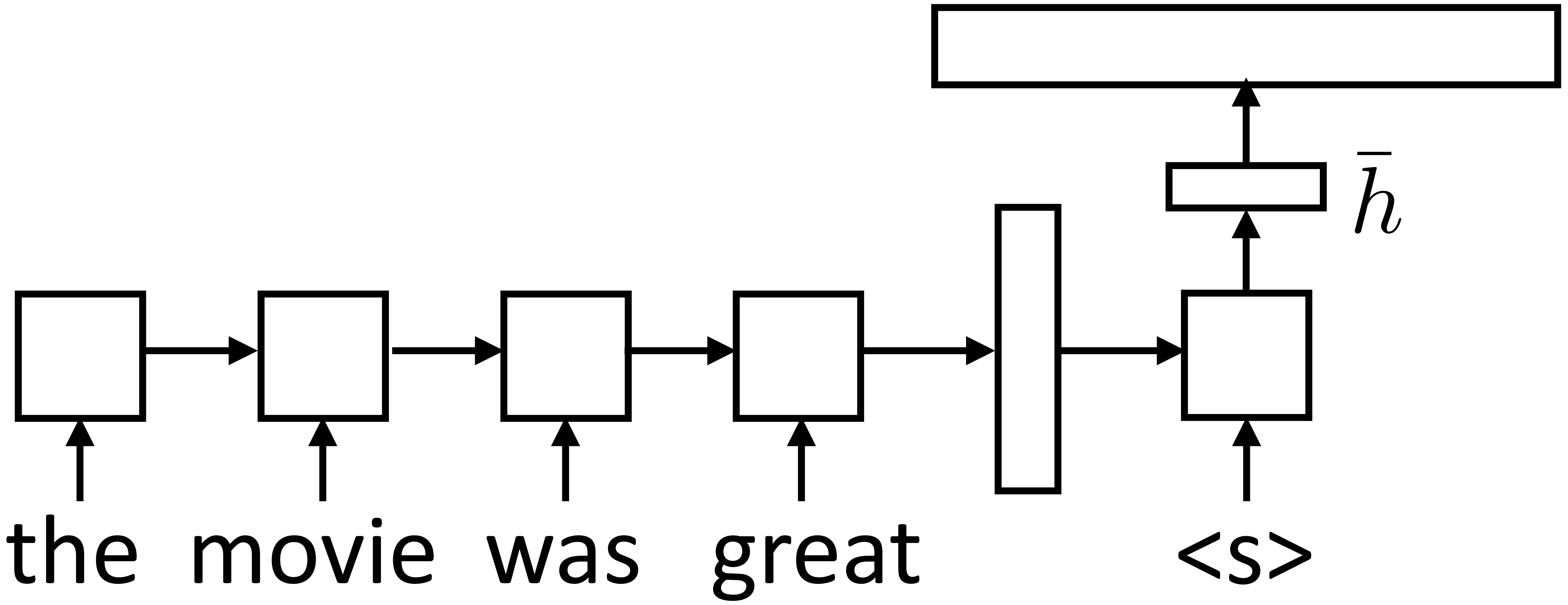
- W size is |vocab| x |hidden state|, softmax over entire vocabulary

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



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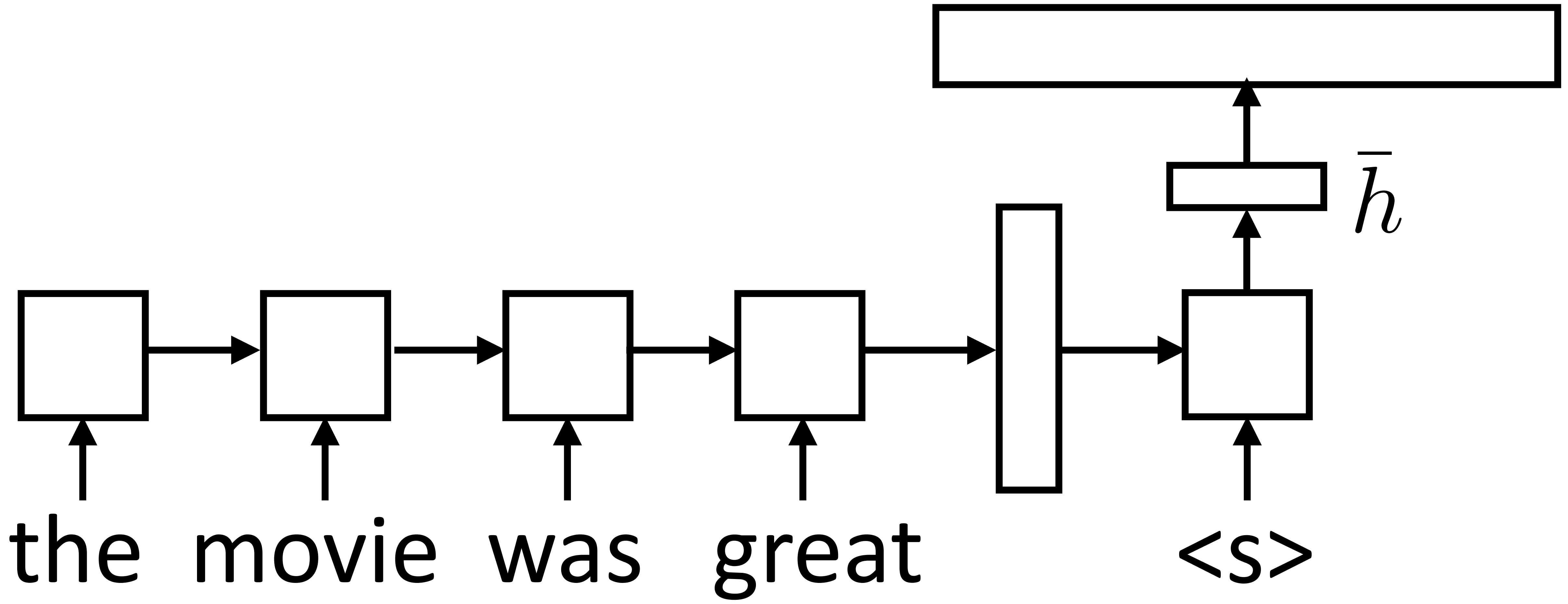

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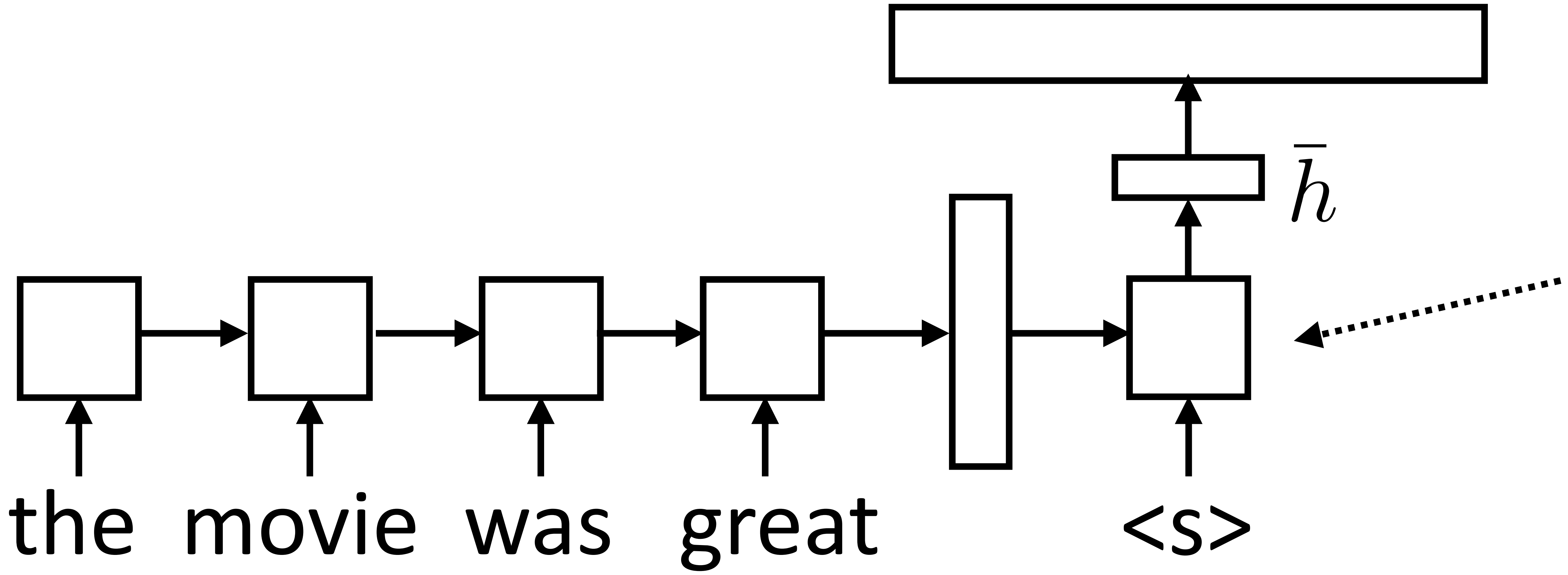

Decoder has separate parameters from encoder, so this can learn to be a language model (produce a plausible next word given current one)

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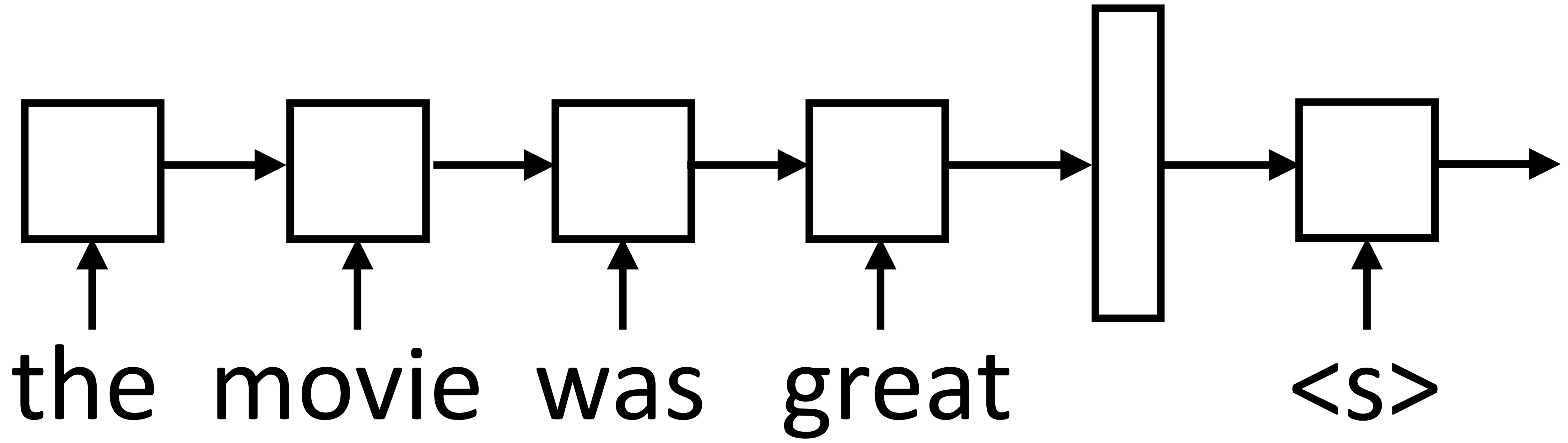

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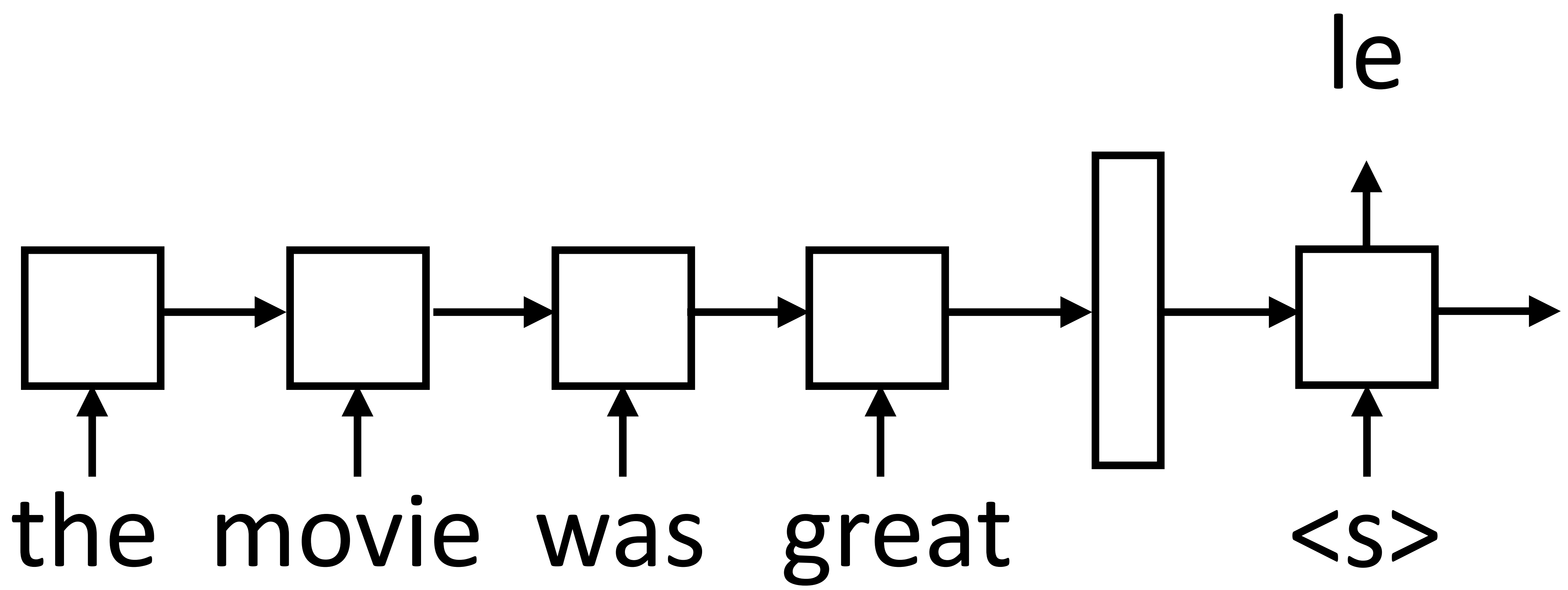

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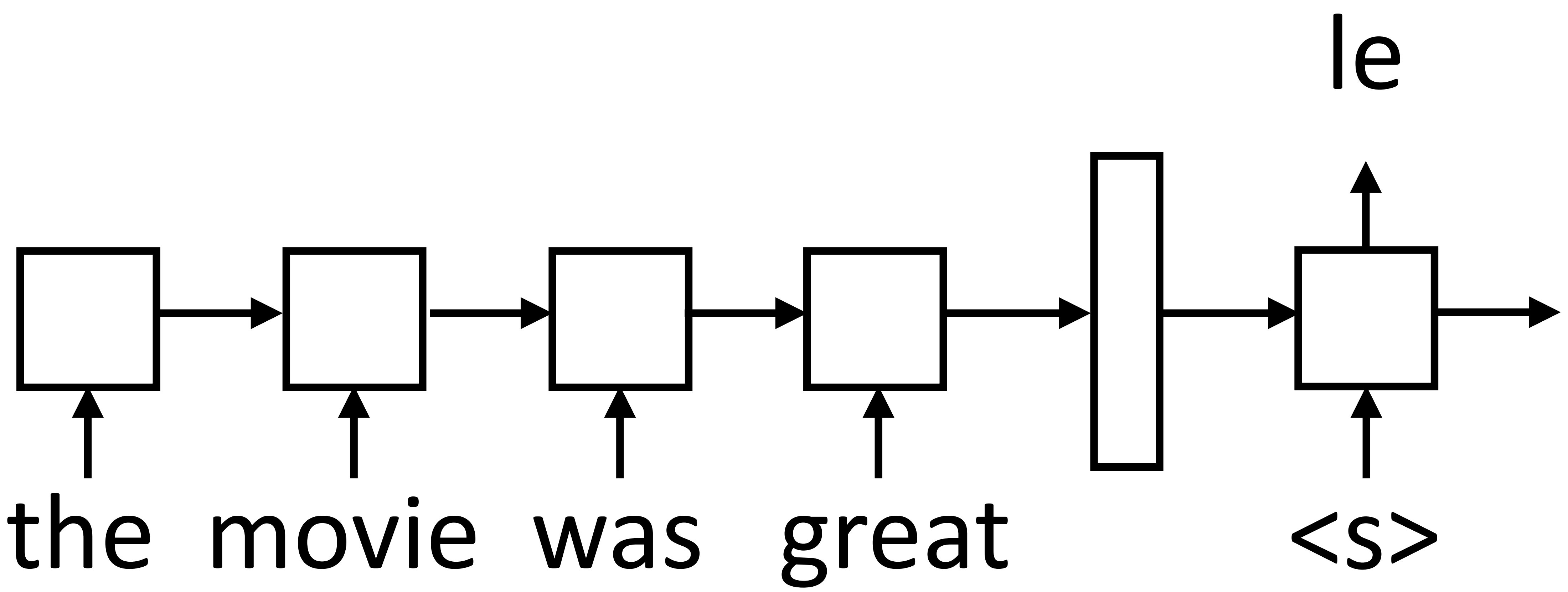

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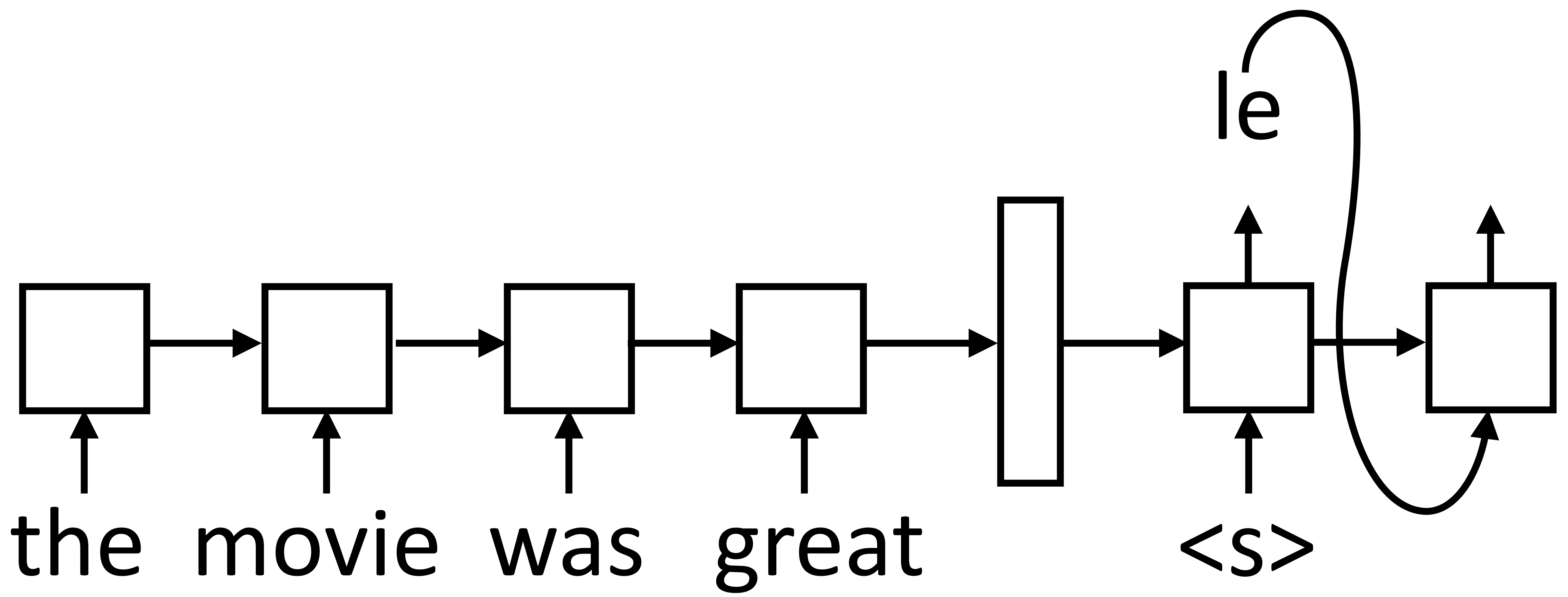

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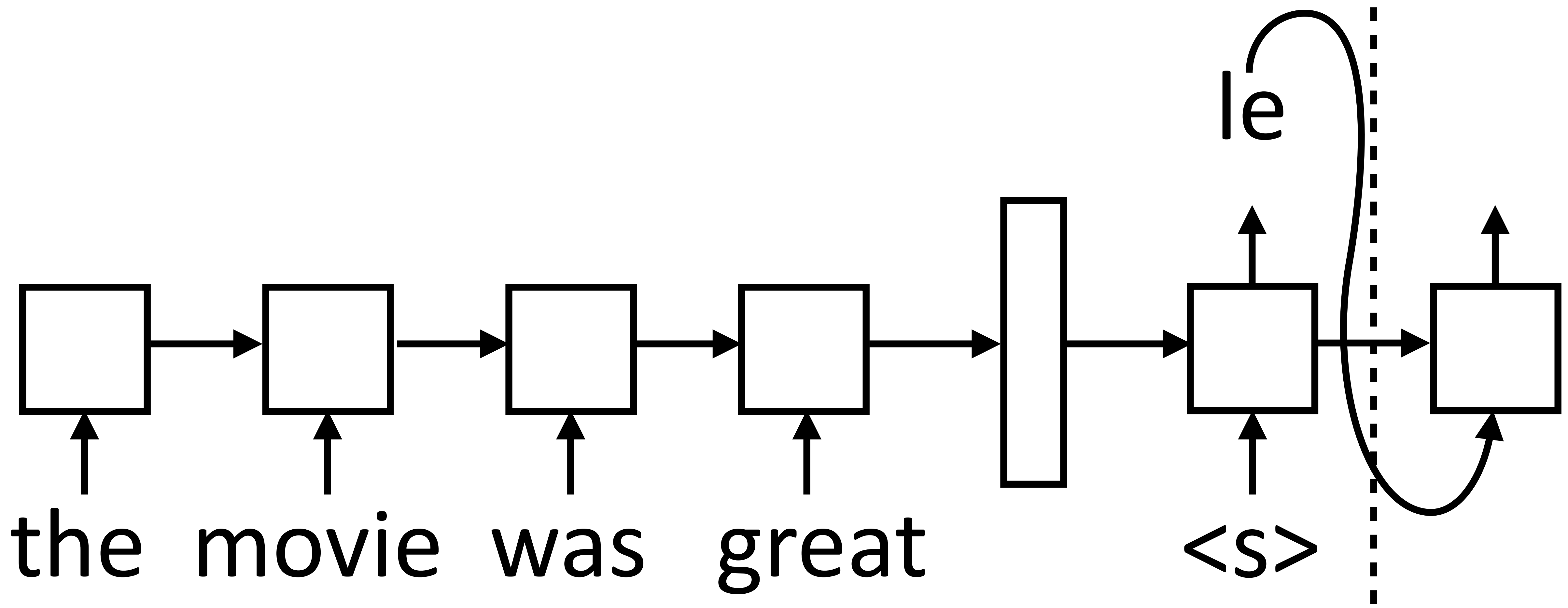

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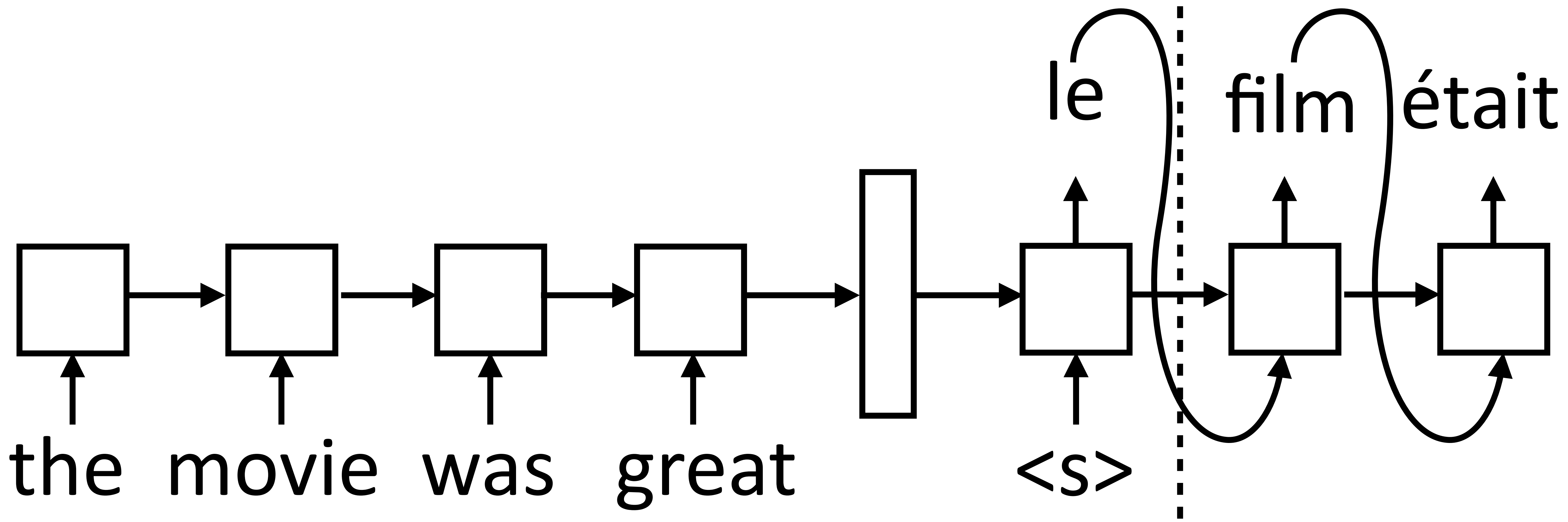

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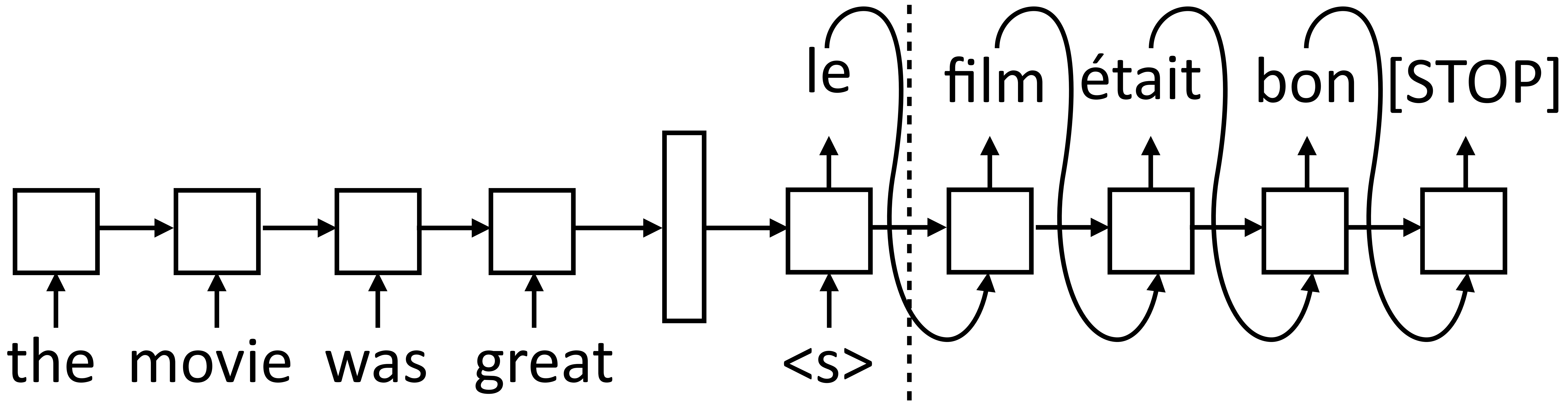

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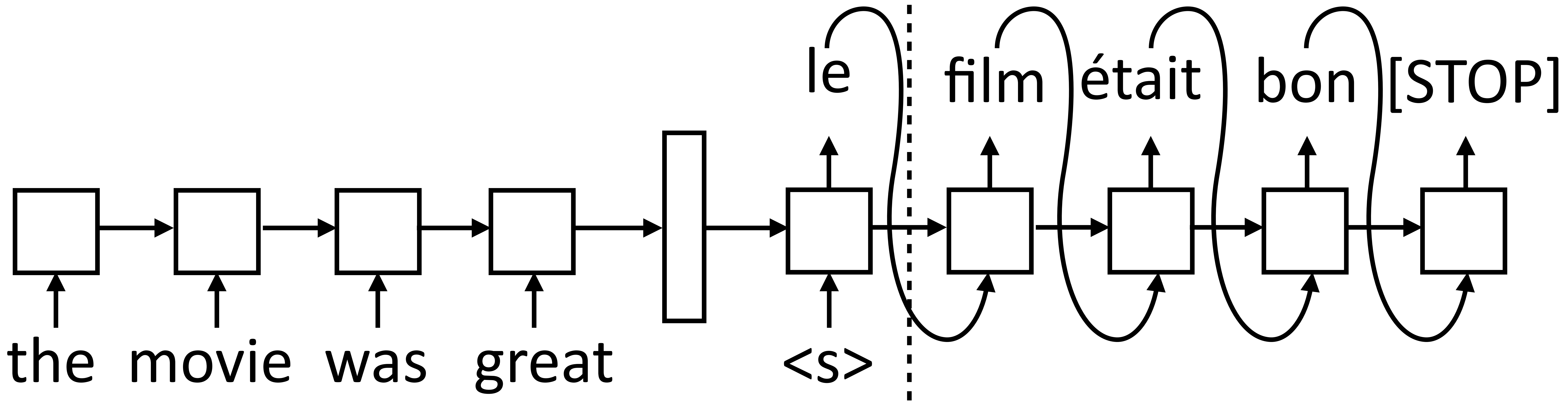
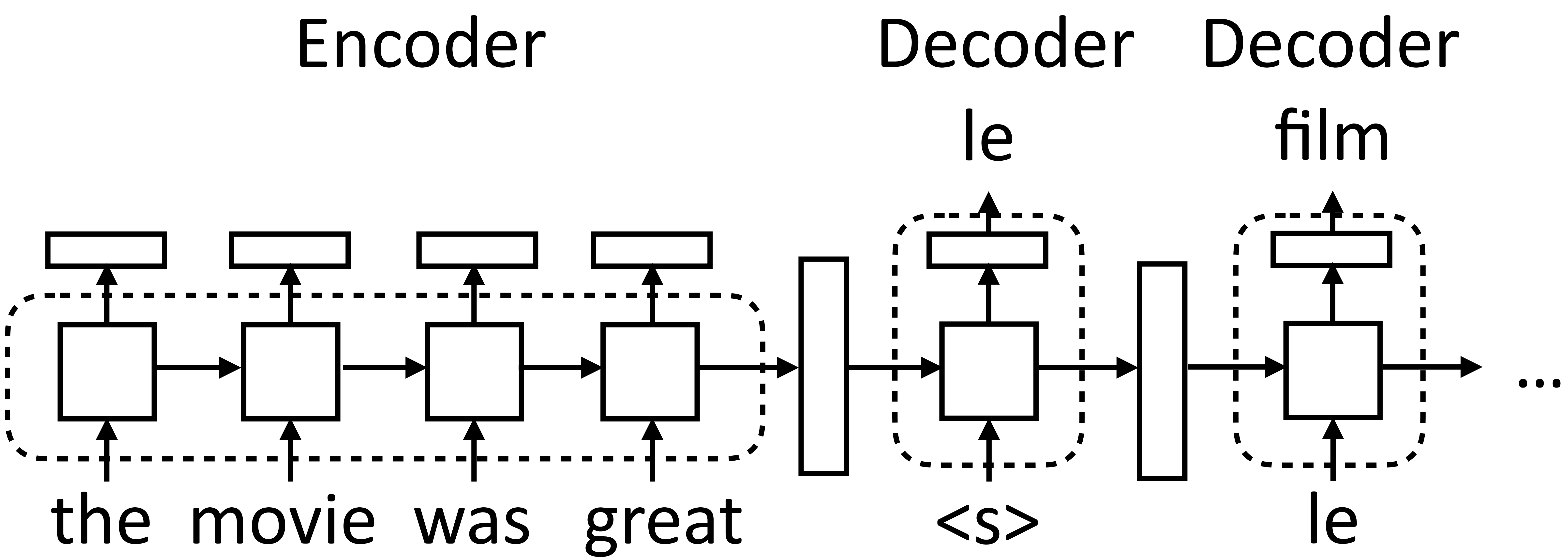


- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models



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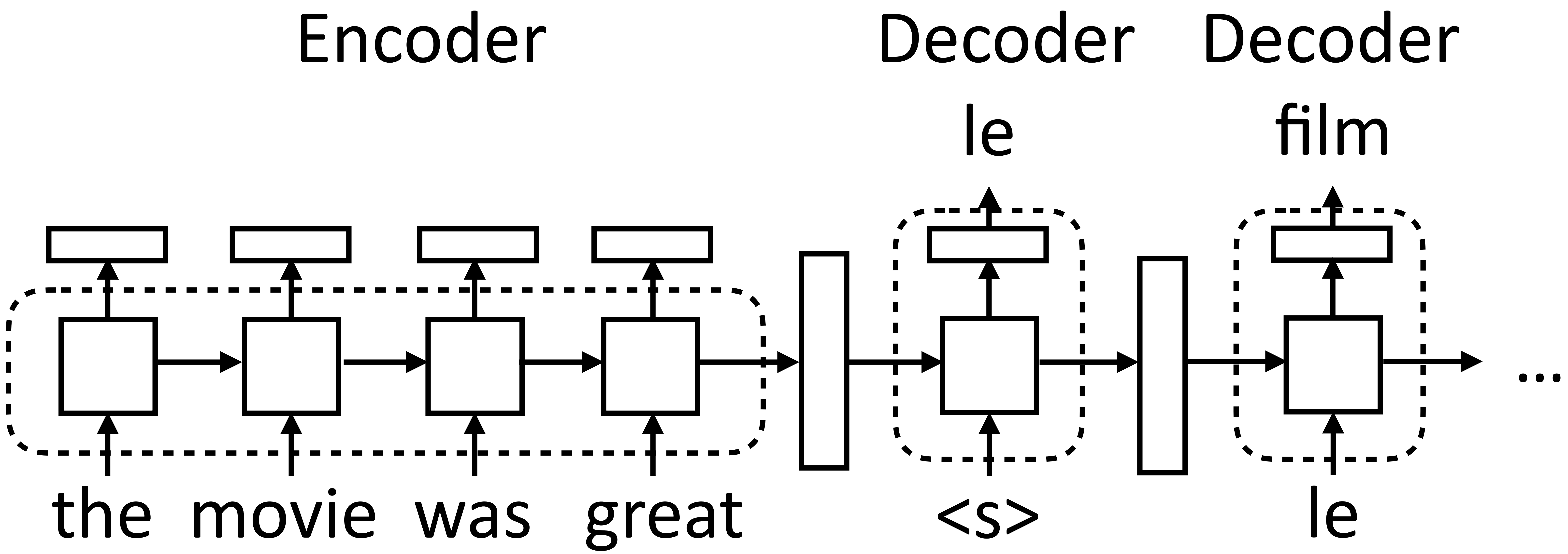

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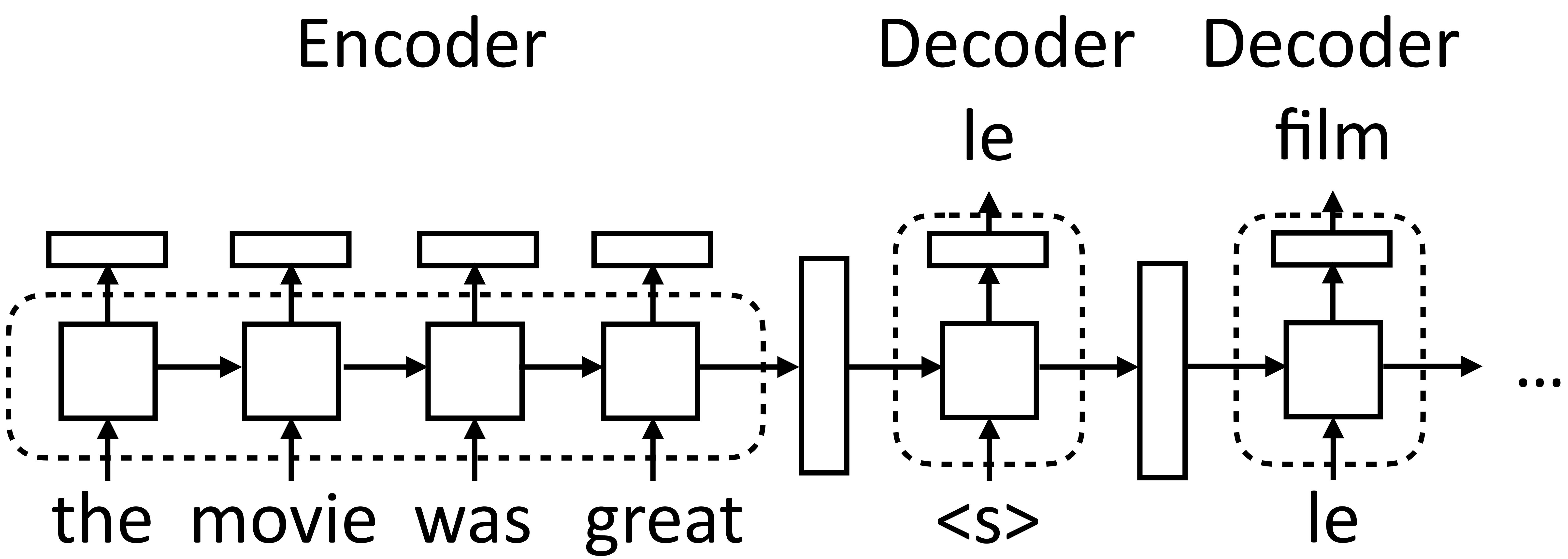

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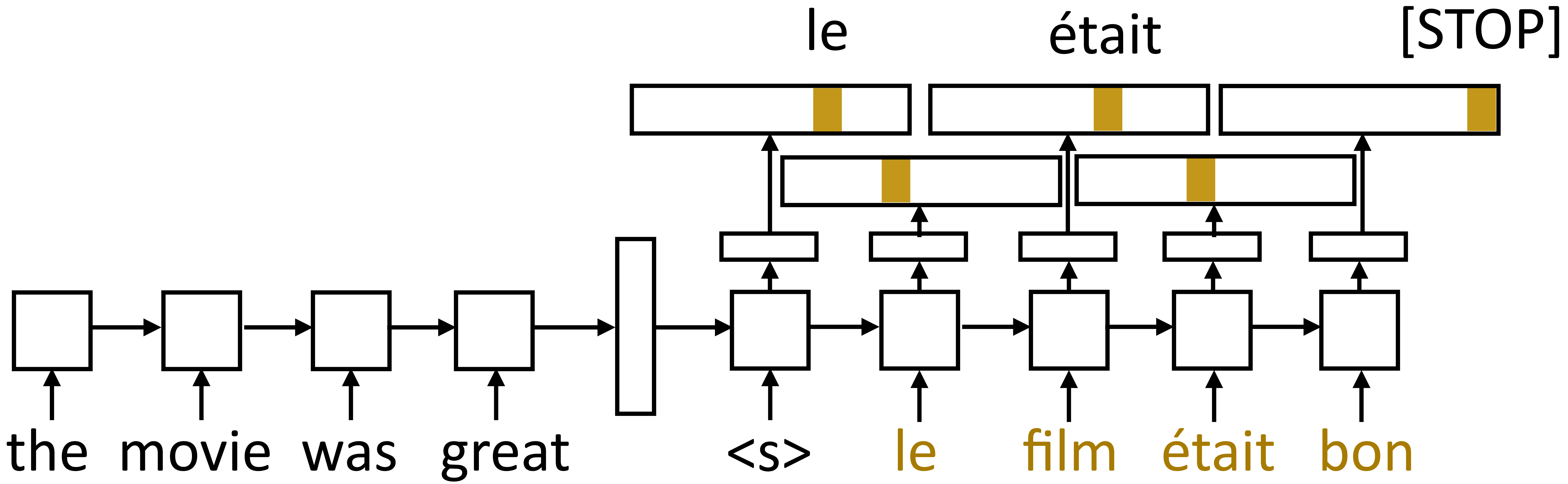
- Decoder: separate module, single cell. Takes two inputs: hidden state (vector h or tuple (h, c)) and previous token. Outputs token + new state

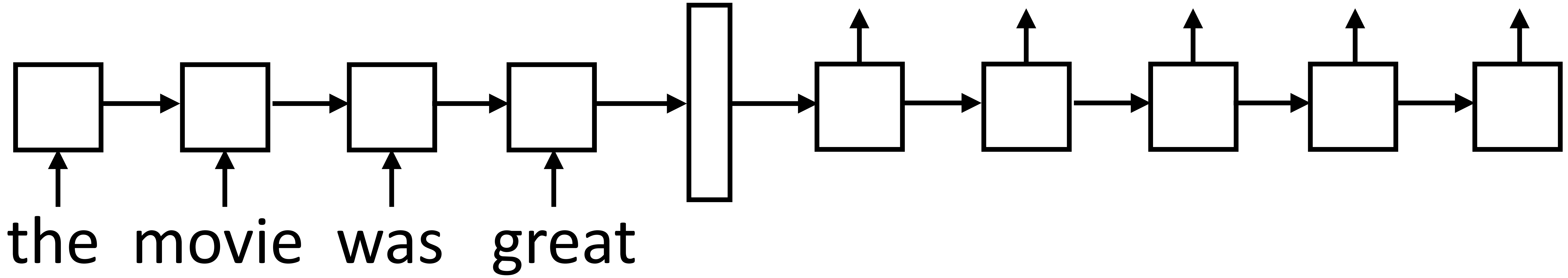
Training



- Objective: maximize $\sum_{(\mathbf{x},\mathbf{y})} \sum_{i=1}^{n} \log P(y_i^* | \mathbf{x}, y_1^*, \ldots, y_{i-1}^*)$
- 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



Bengio et al. (2015)

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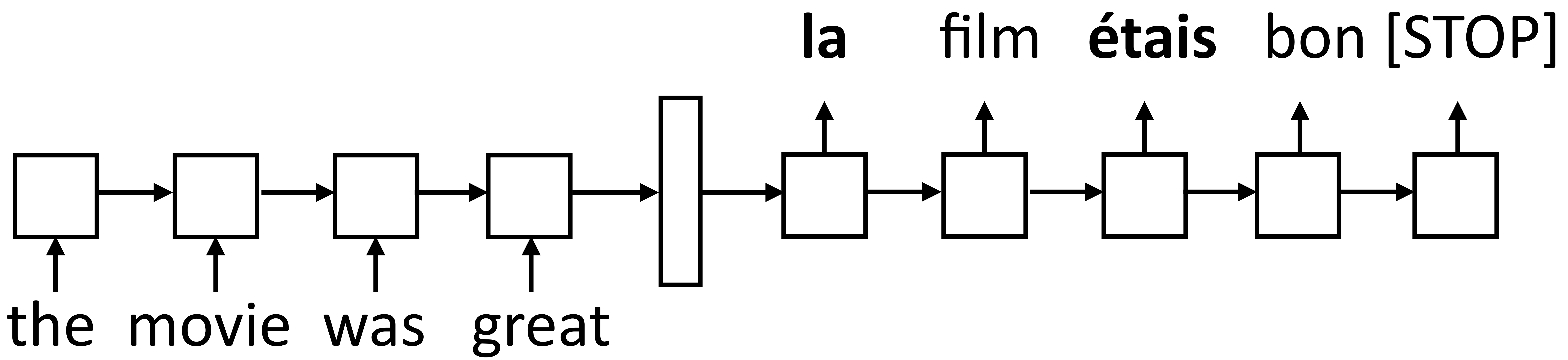

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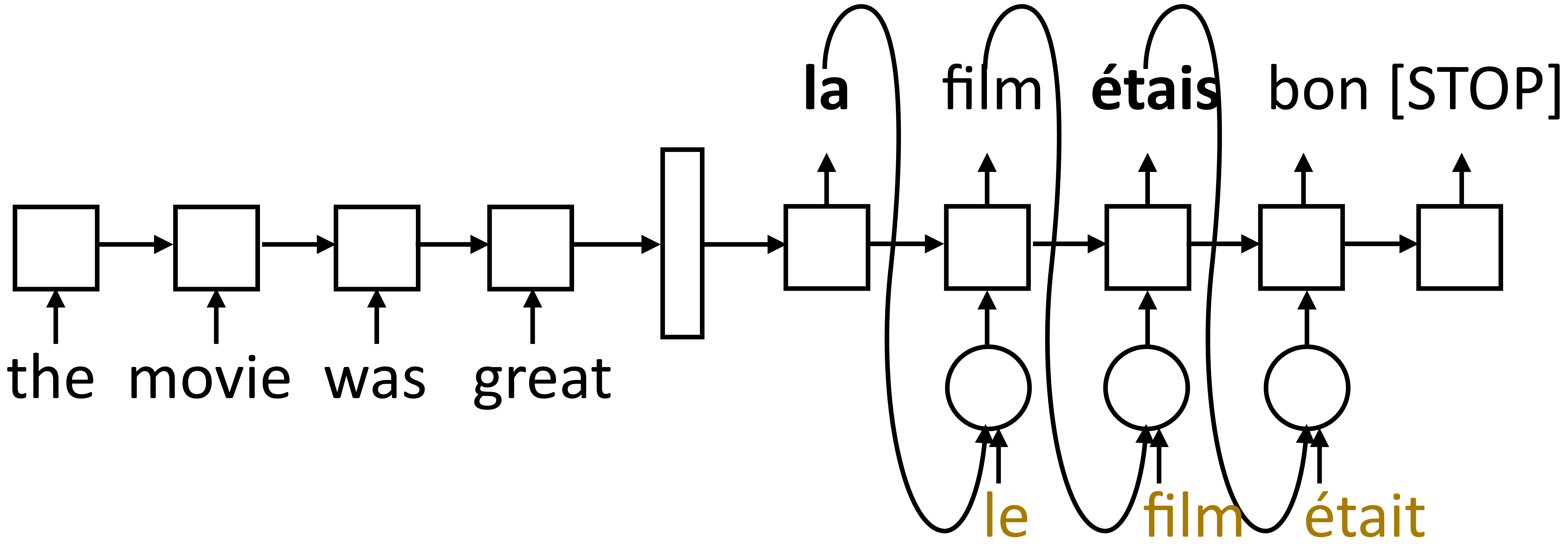

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Bengio et al. (2015)

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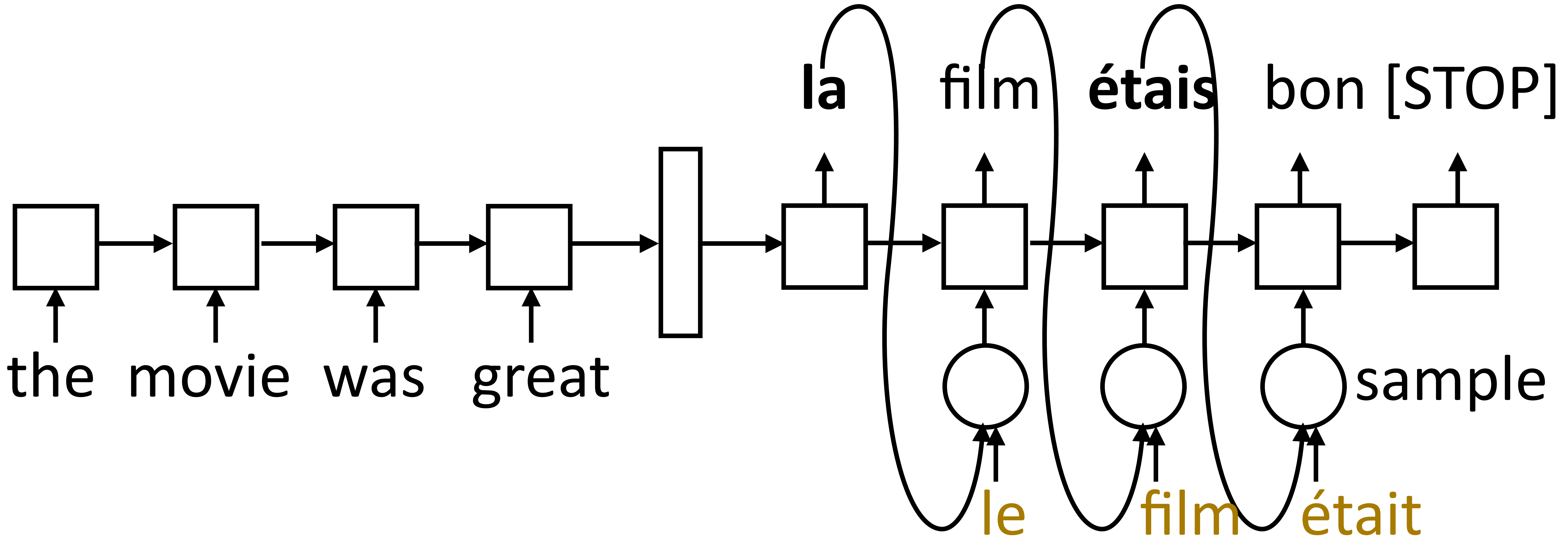

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- Starting with *p* = 1 and decaying it works best

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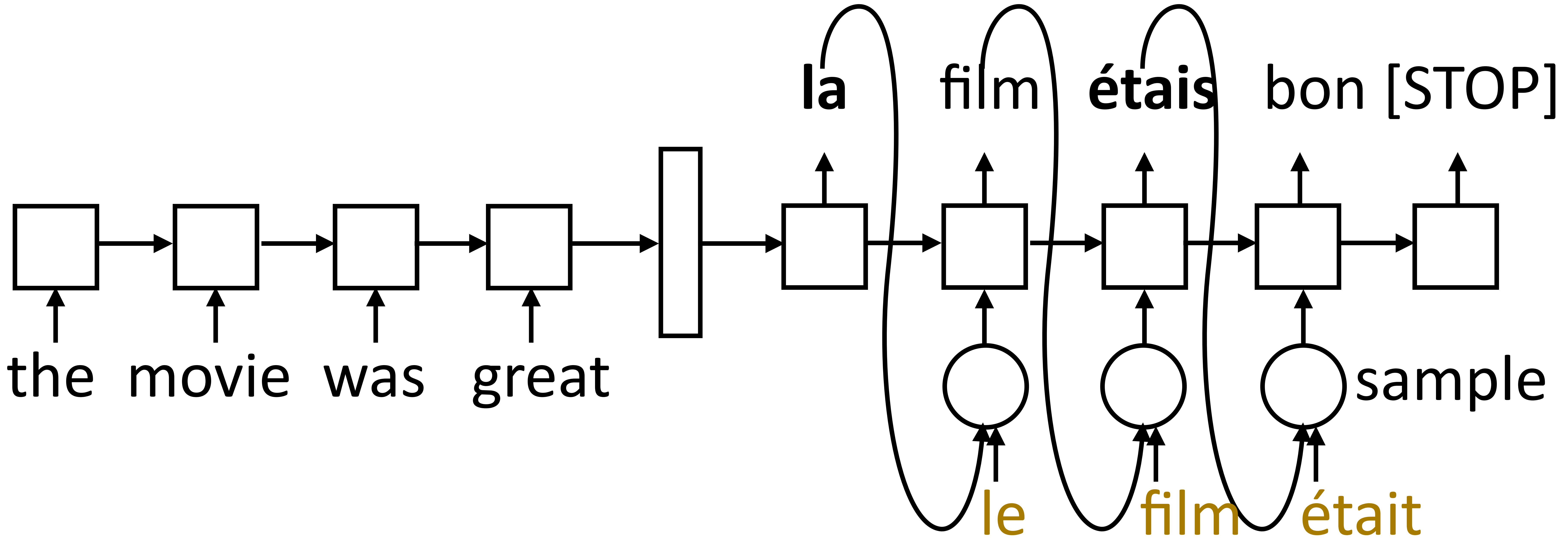

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- Ideally (in theory), use RL for this…

Bengio et al. (2015)

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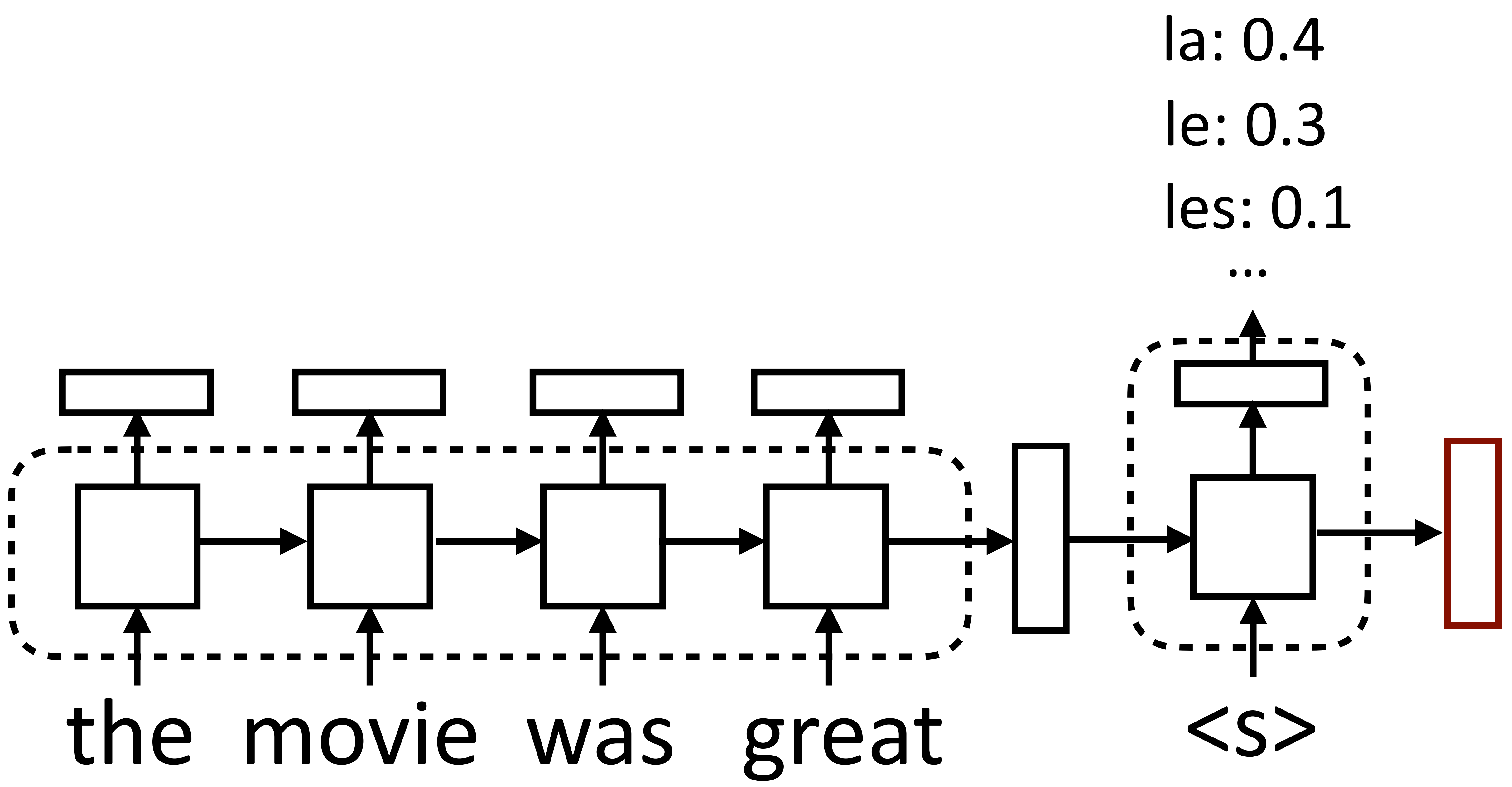
- Encoder: Can be a CNN/LSTM/Transformer…
- Decoder: also flexible in terms of architecture (more later). Execute one step of computation at a time, so computation graph is formulated as taking one input + hidden state
- Beam search: can help with lookahead. Finds the (approximate) highest scoring sequence:

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

Beam Search

- Maintain decoder state, token history in beam



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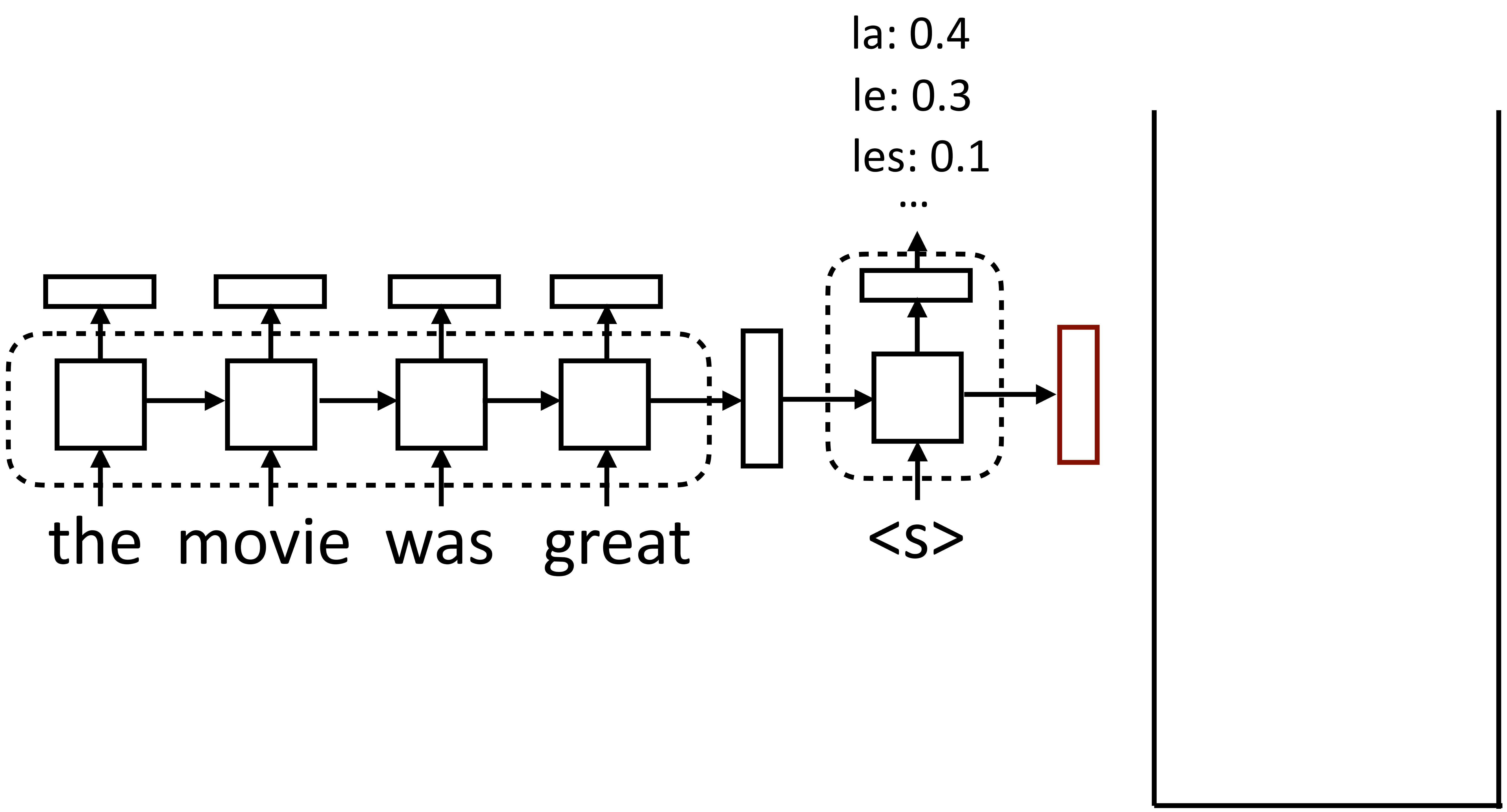

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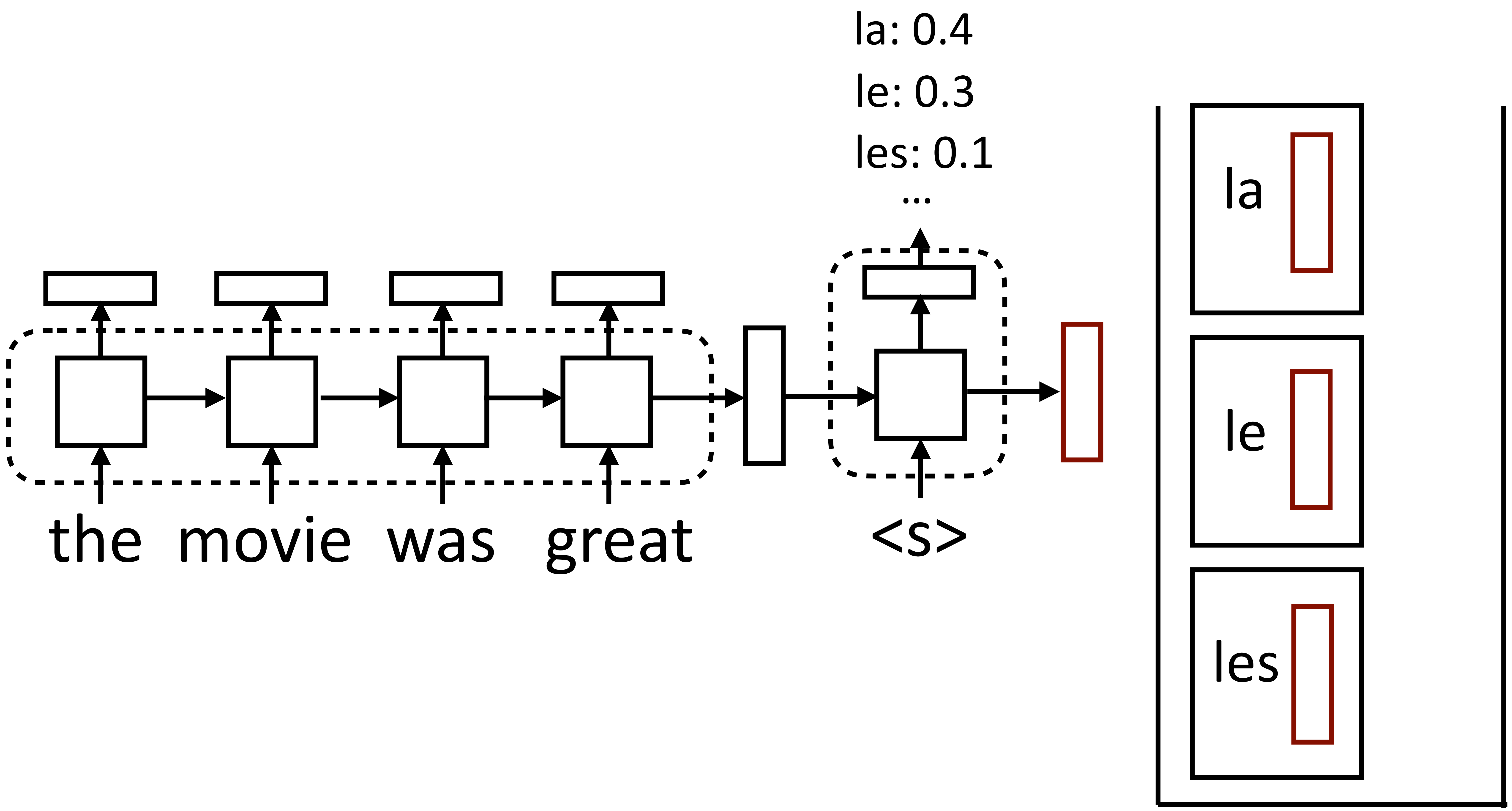

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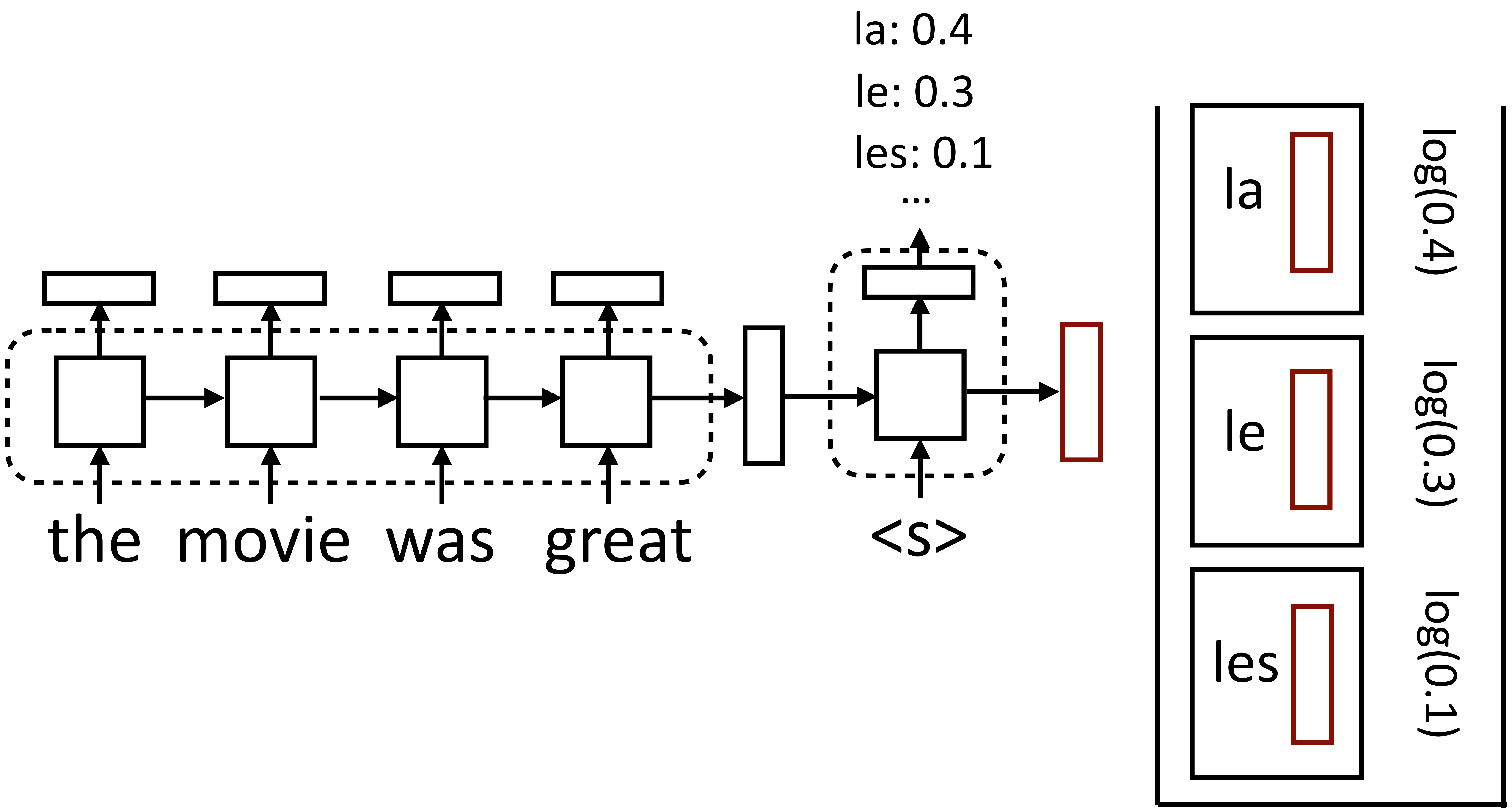

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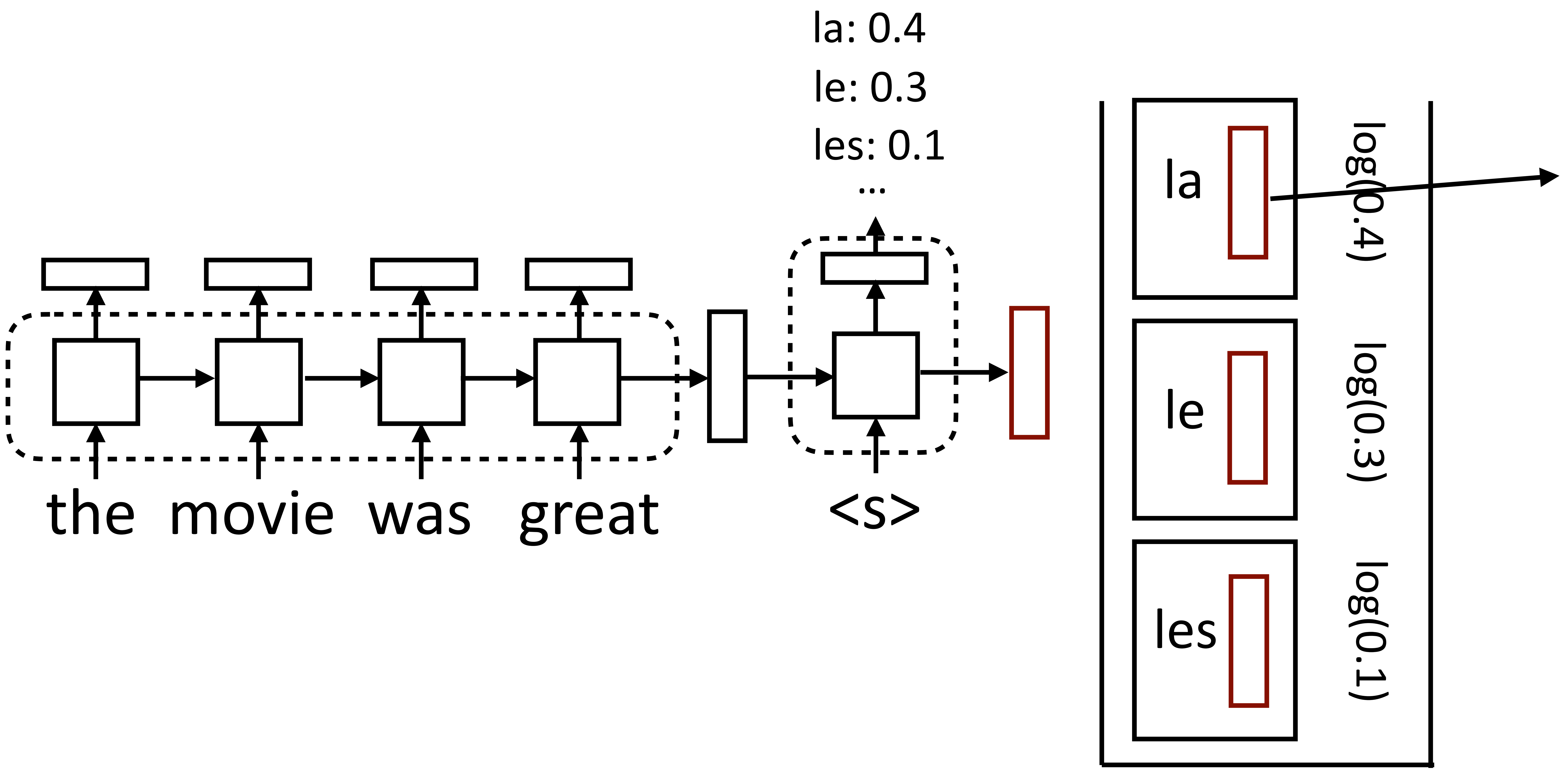

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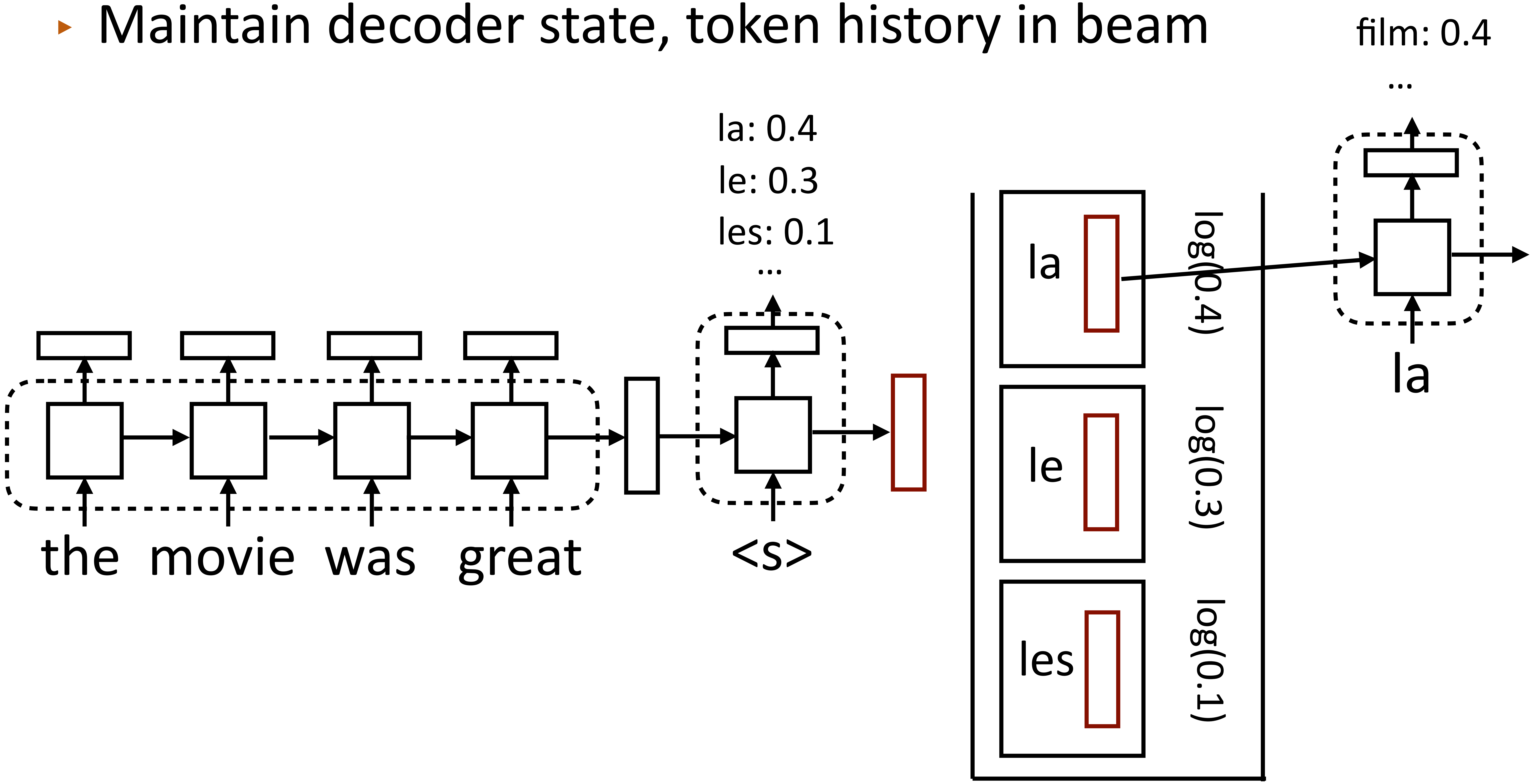

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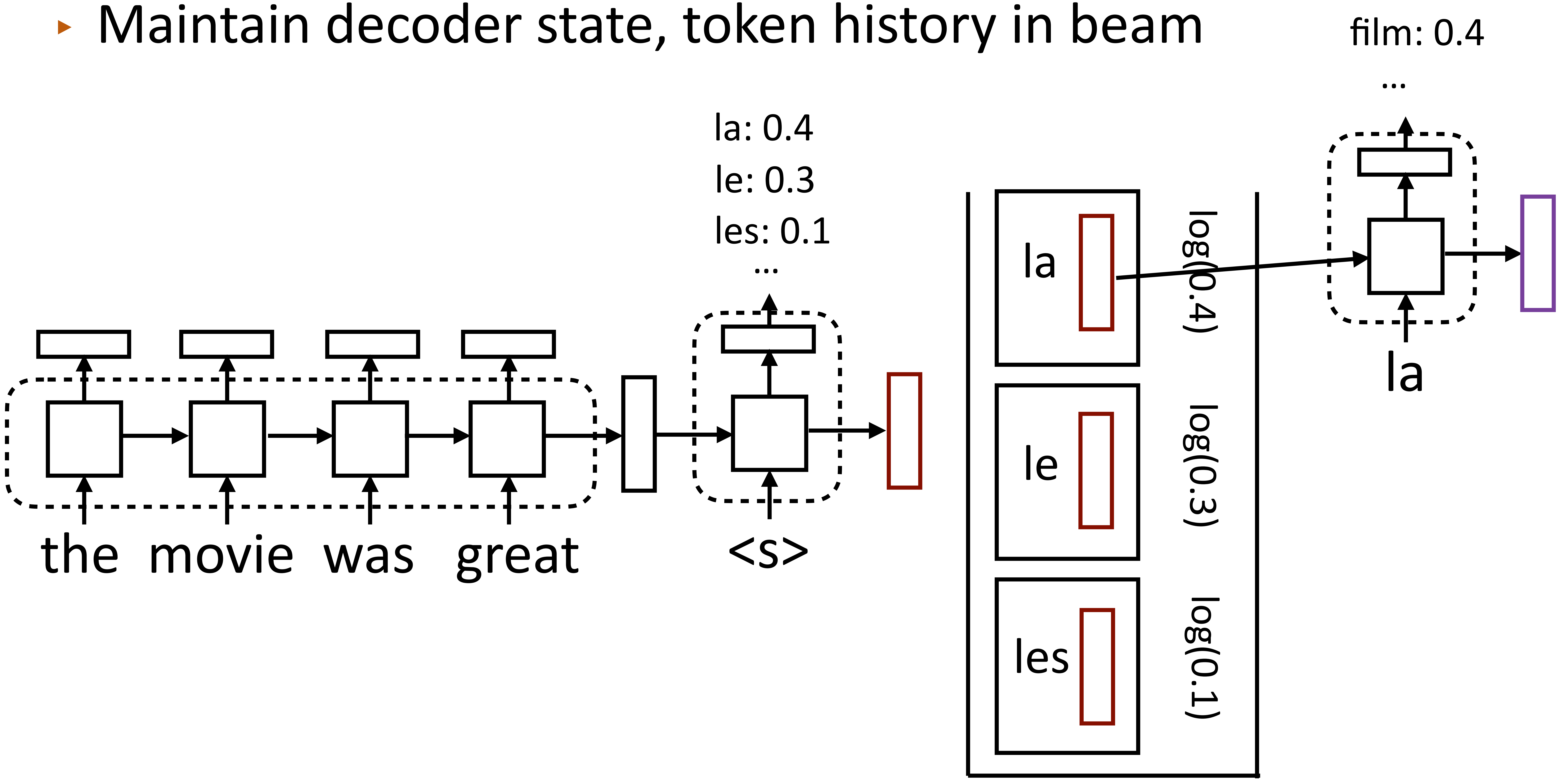

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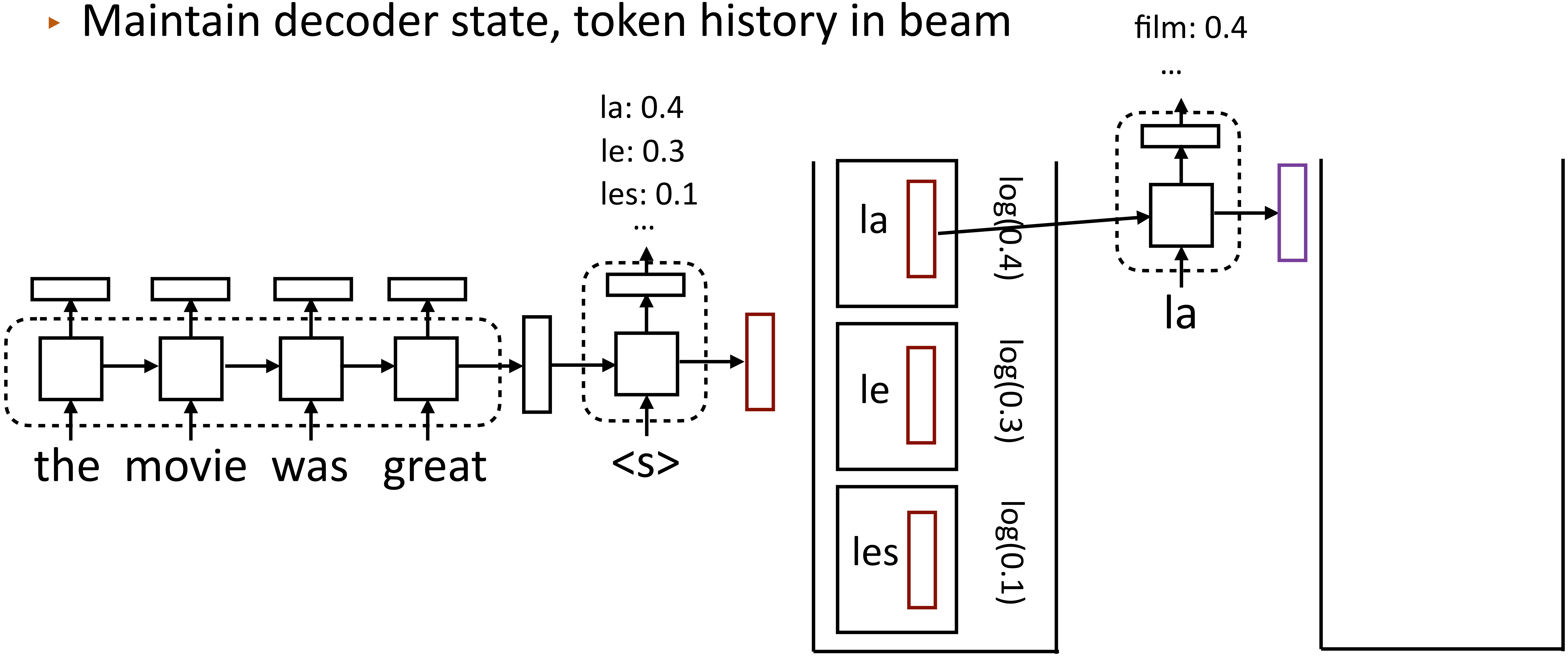

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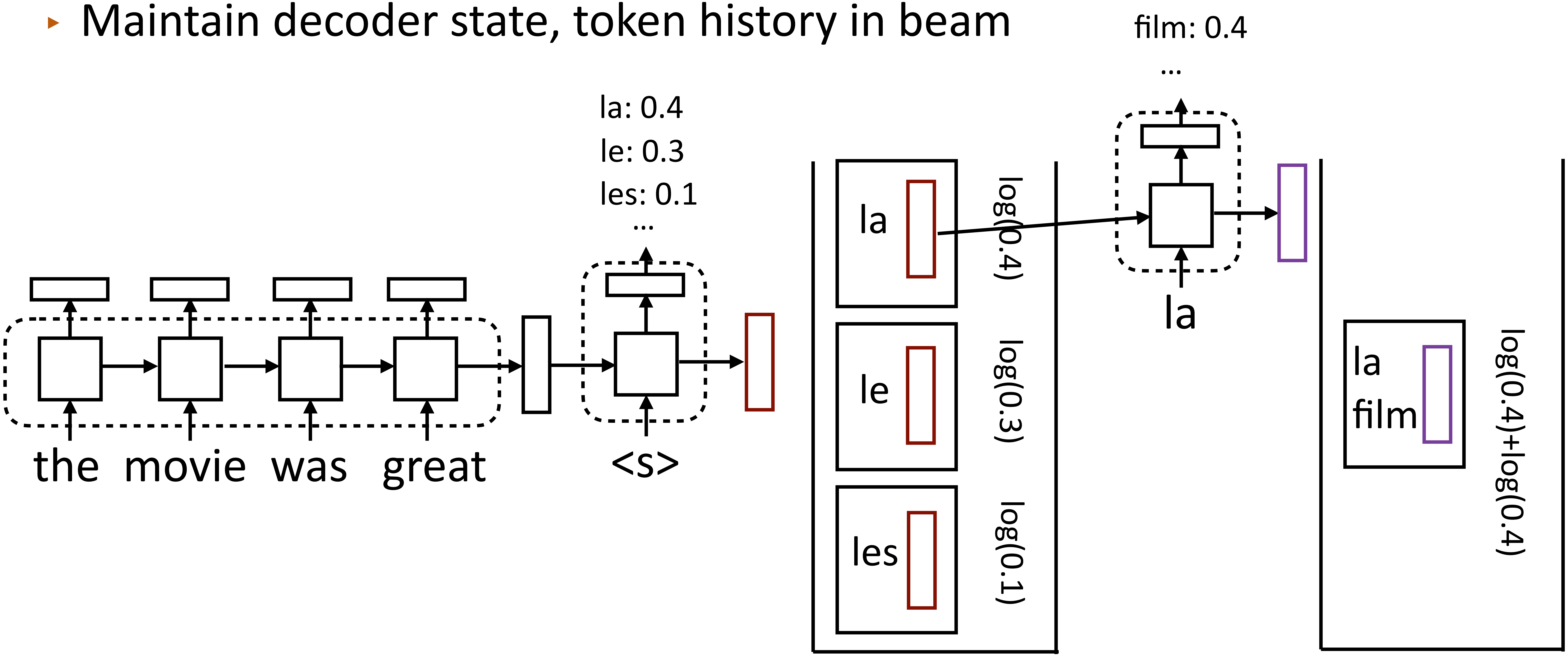

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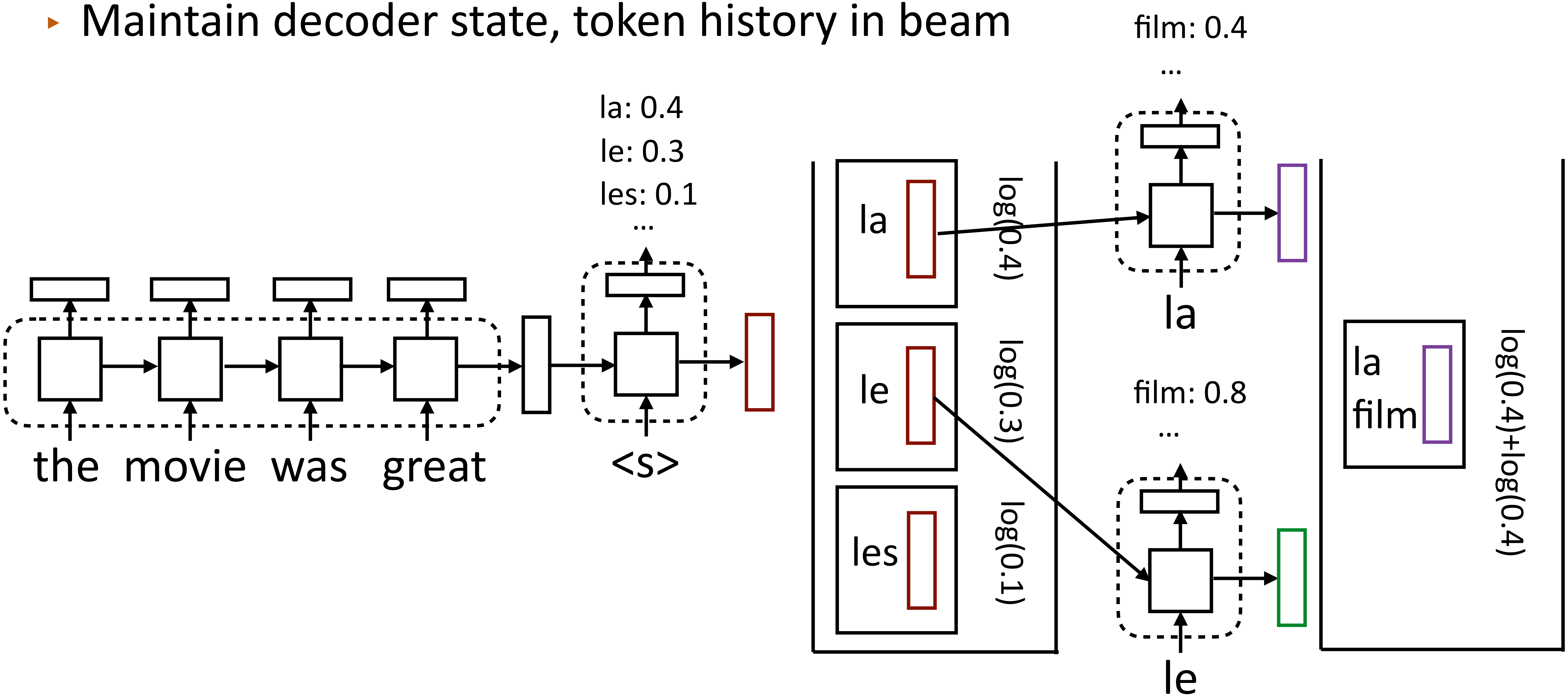

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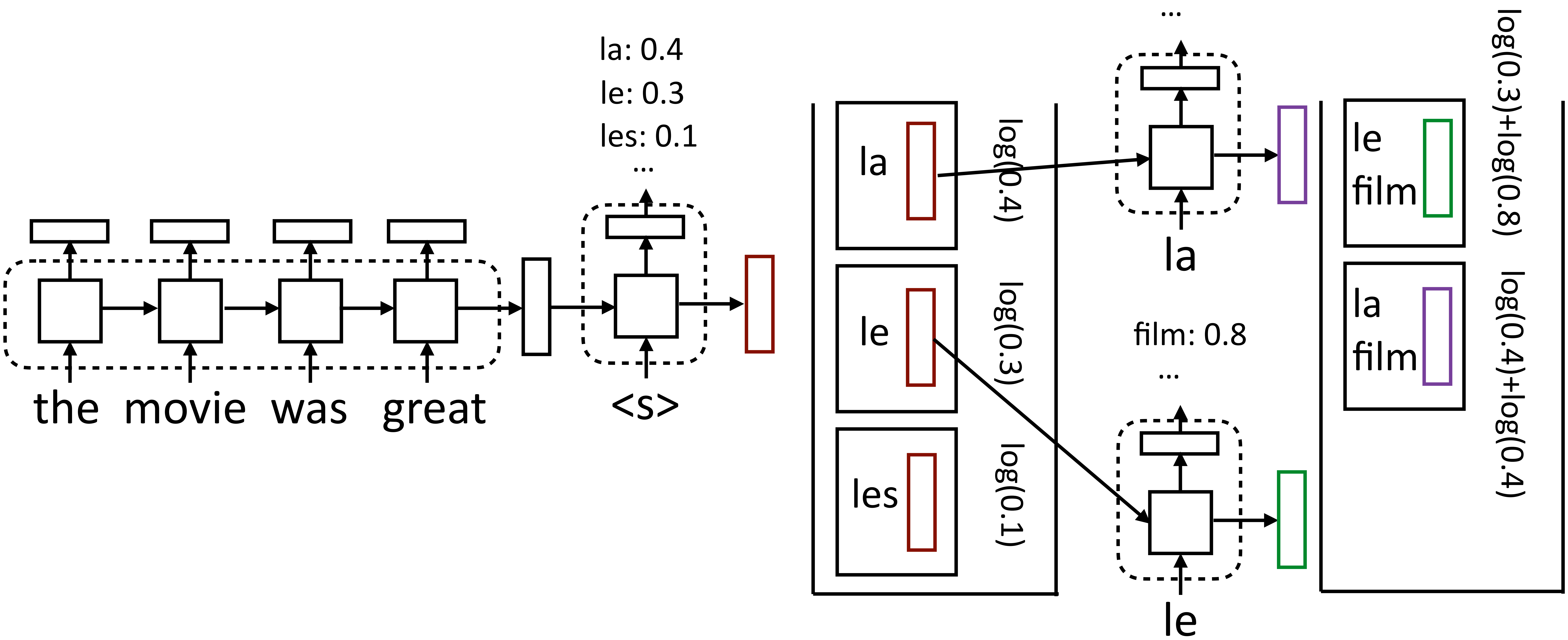

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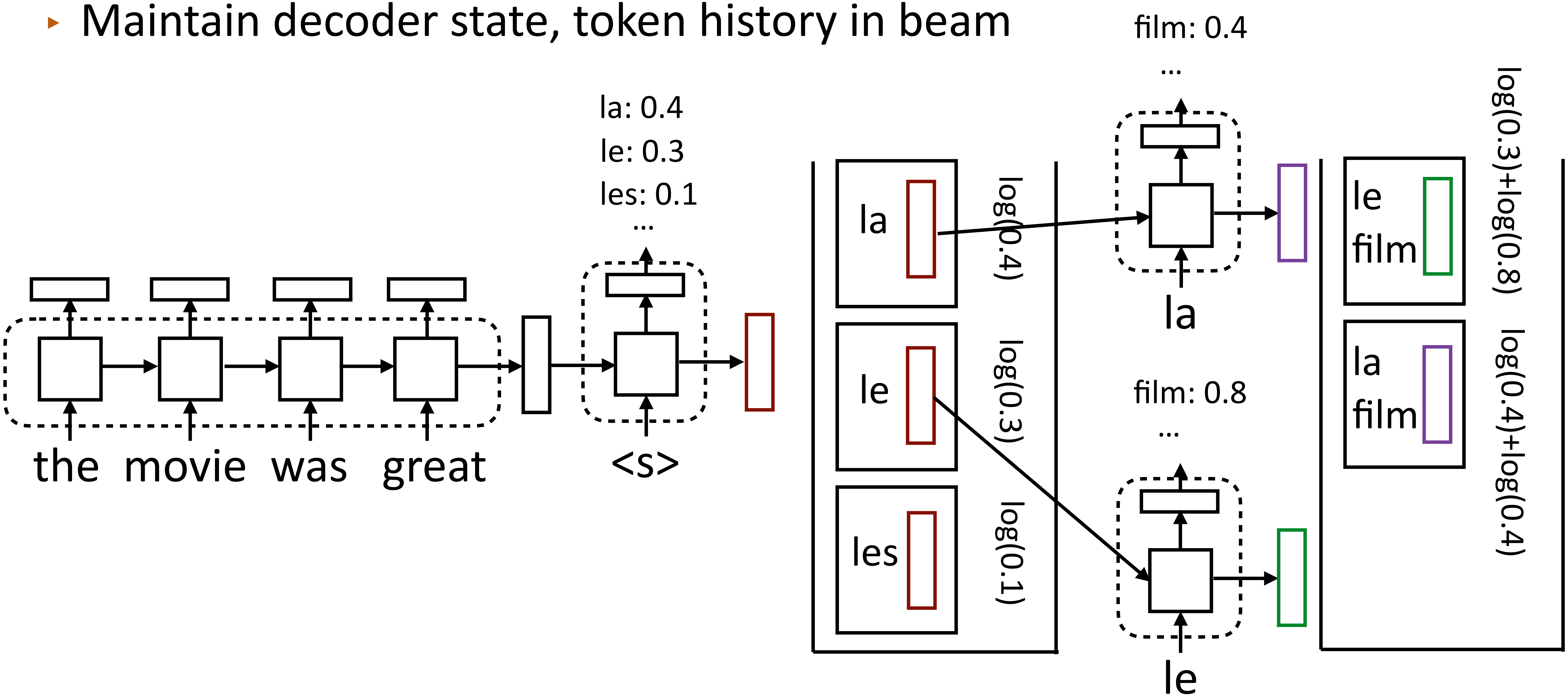

- Do **not** max over the two *film* states! Hidden state vectors are different

Semantic Parsing as Translation

"what states border Texas"

↓

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

Jia and Liang (2015)

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- Write down a linearized form of the semantic parse, train seq2seq models to directly translate into this representation

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- Write down a linearized form of the semantic parse, train seq2seq models to directly translate into this representation
- No need to have an explicit grammar, simplifies algorithms
- Might not produce well-formed logical forms, might require lots of data

Jia and Liang (2015)

Regex Prediction

Locascio et al. (2016)

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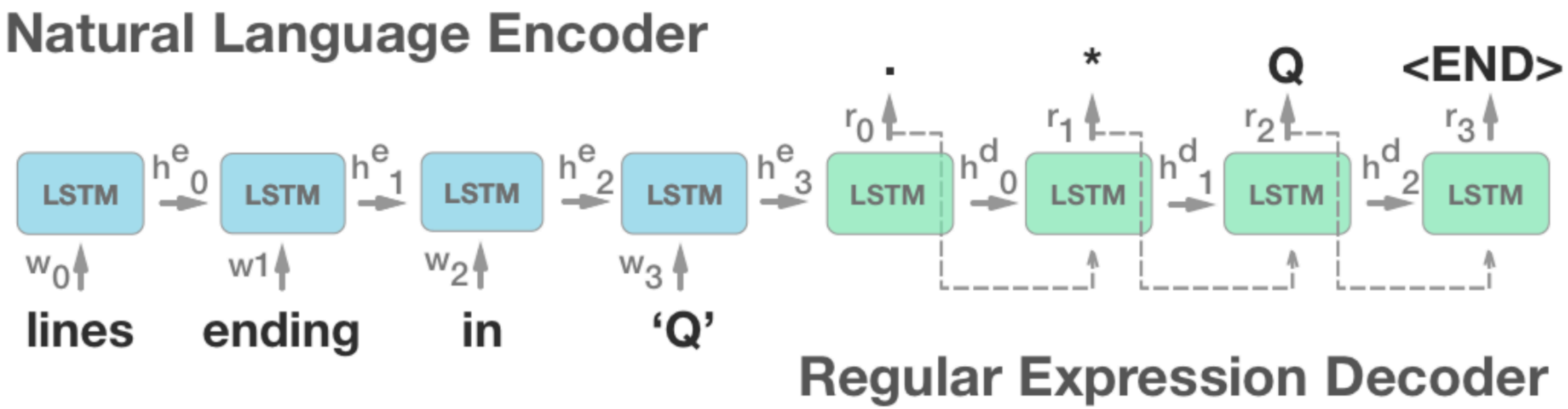

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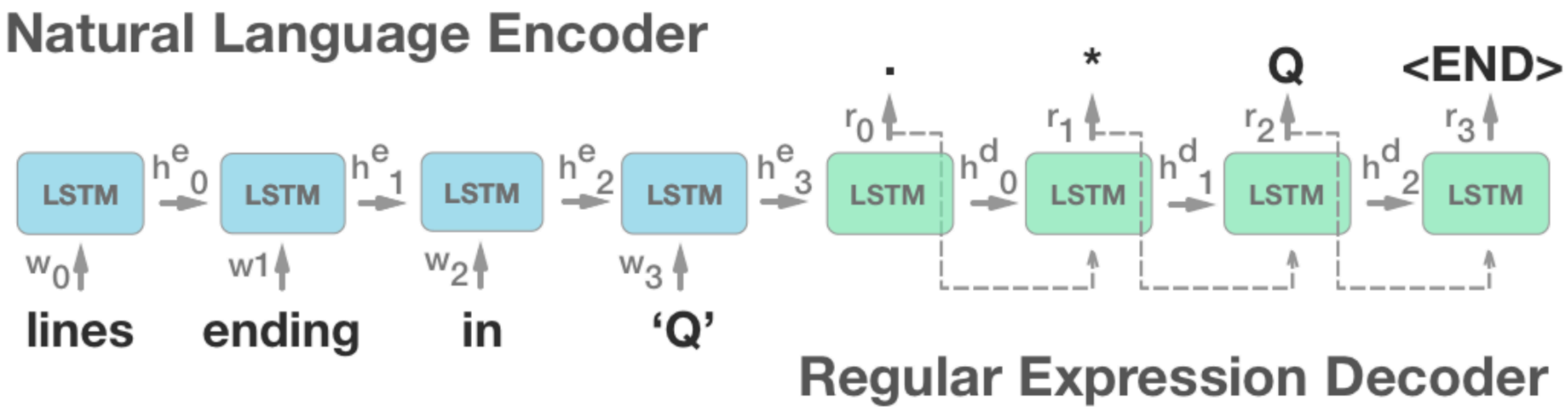

- Problem: requires a lot of data: 10,000 examples needed to get ~60% accuracy on pretty simple regexes

Locascio et al. (2016)

SQL Generation

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

Question:

How many CFL teams are from York College?

SQL:

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SELECT COUNT CFL Team FROM
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Zhong et al. (2017)

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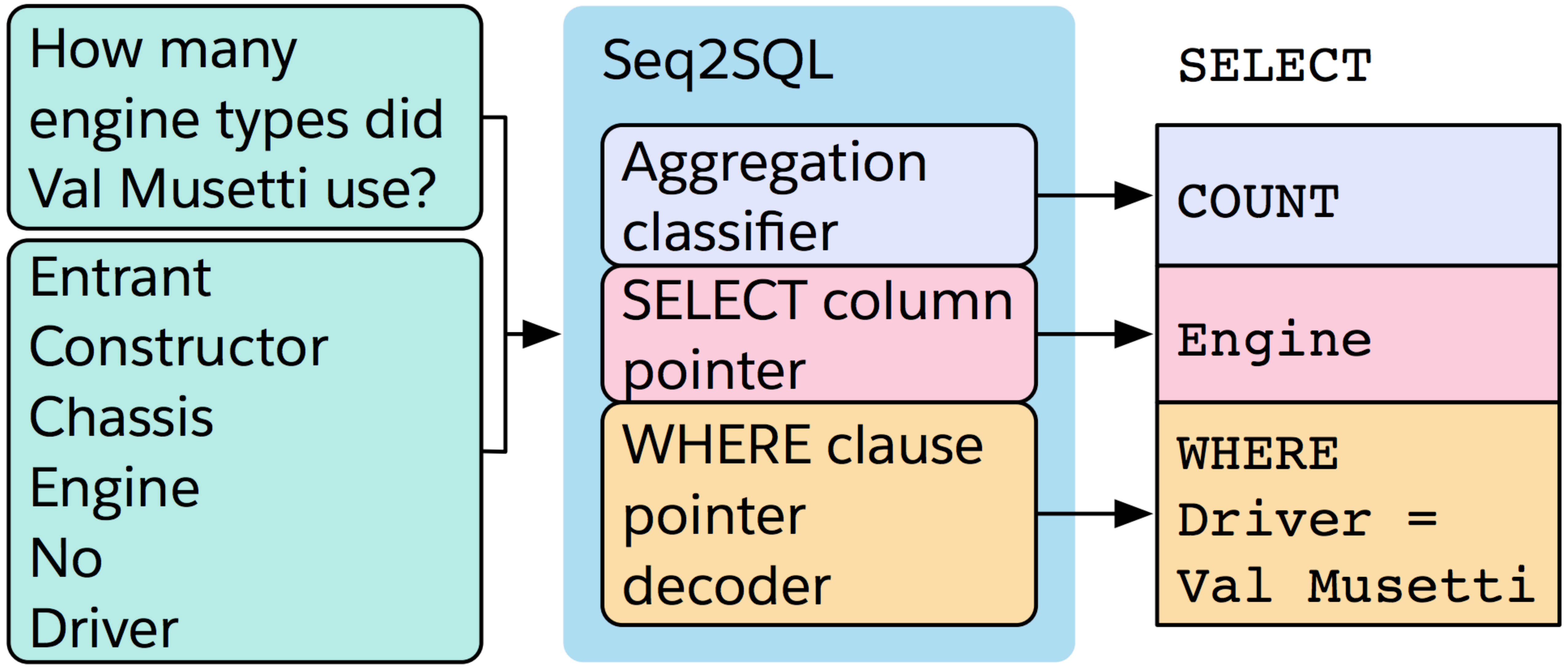

Zhong et al. (2017)

SQL Generation

- Convert natural language description into a SQL query against some DB
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How many CFL teams are from York College?

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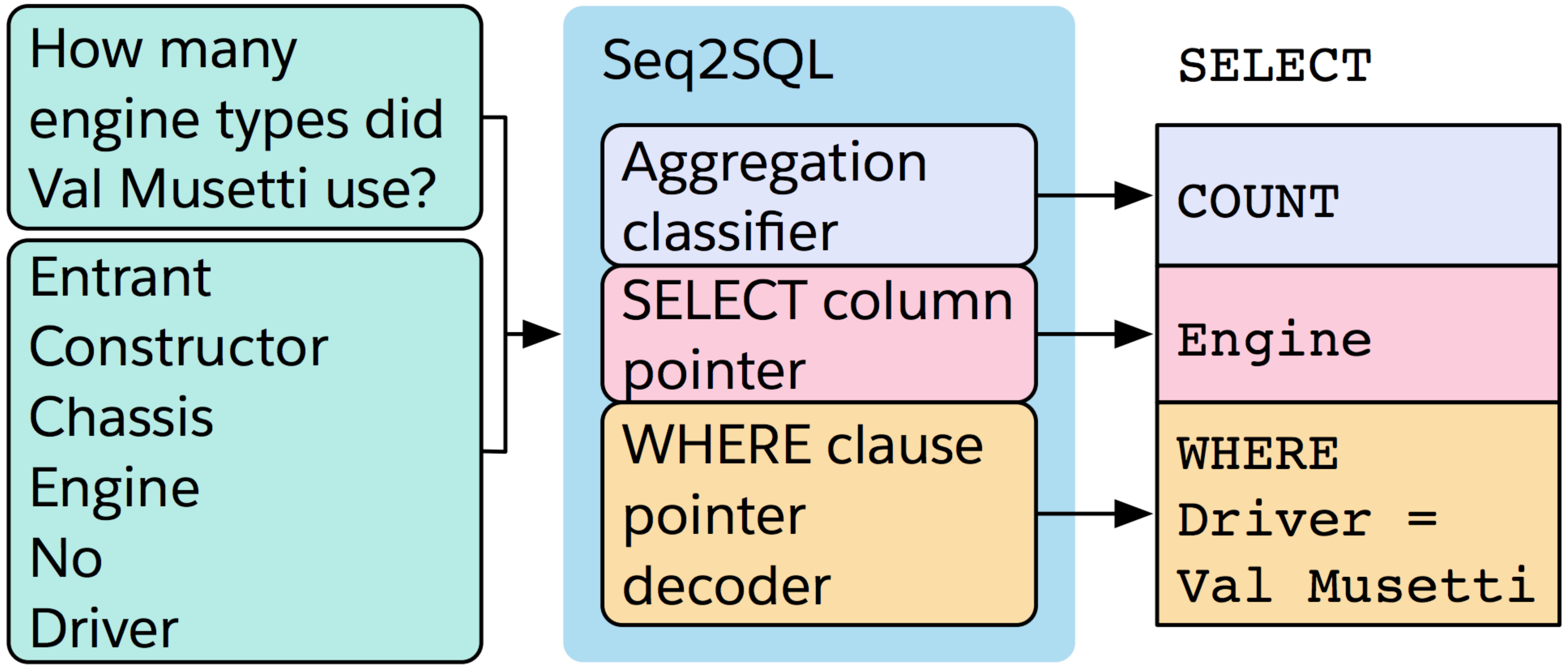

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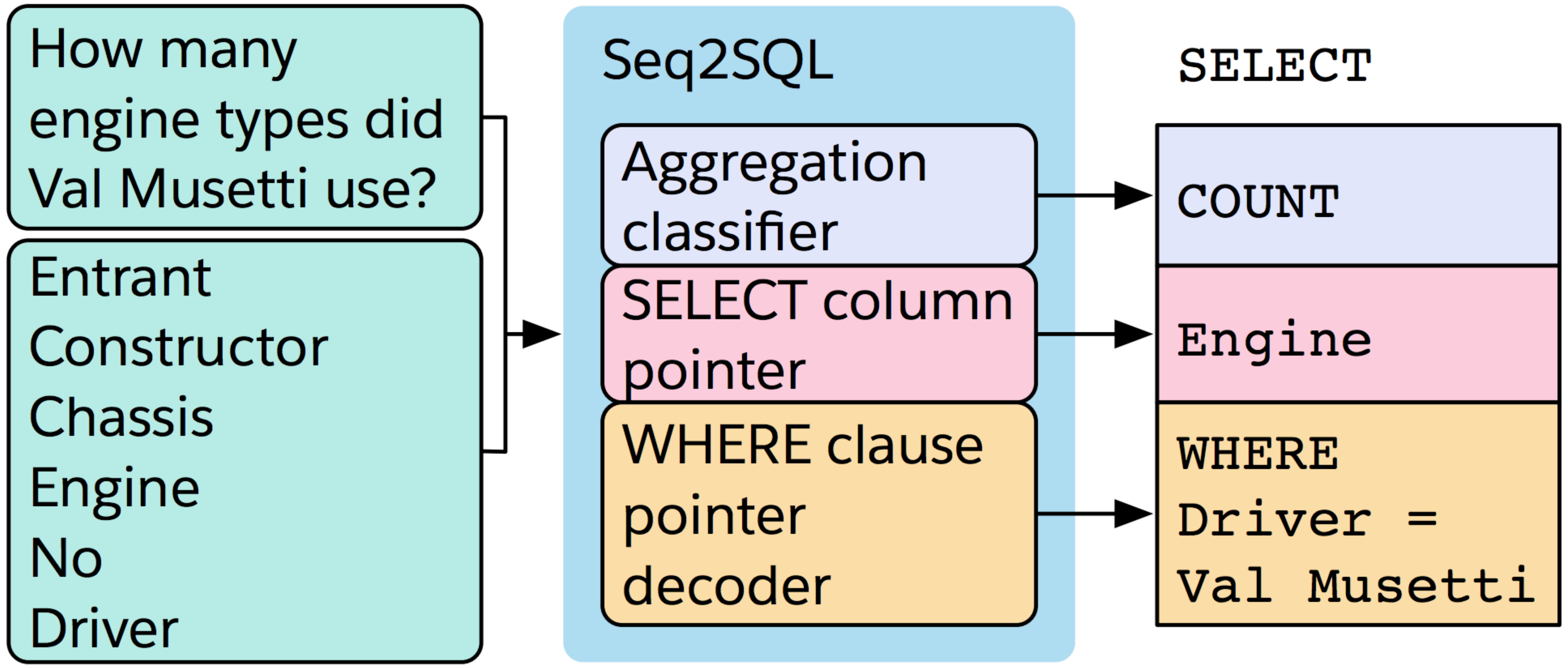

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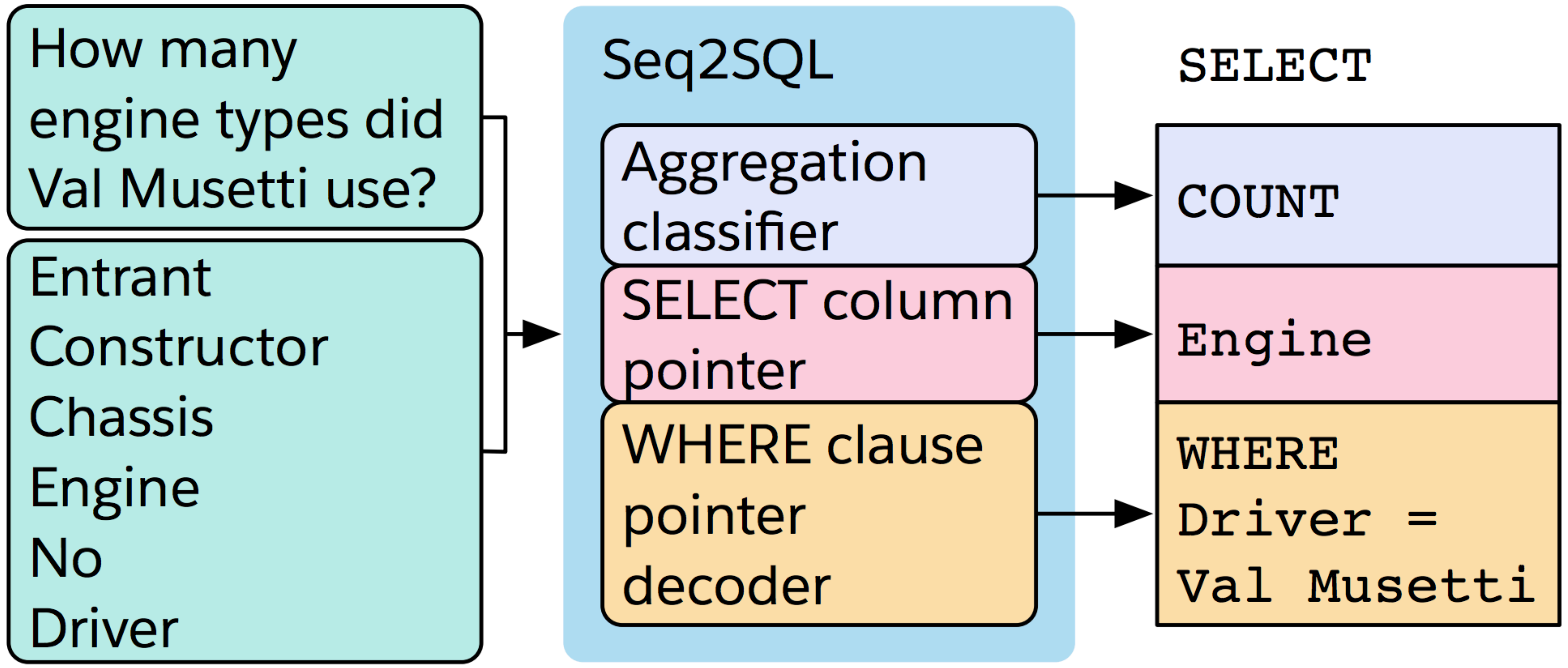

Zhong et al. (2017)

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  - Three seq2seq models
- How to capture column names + constants?
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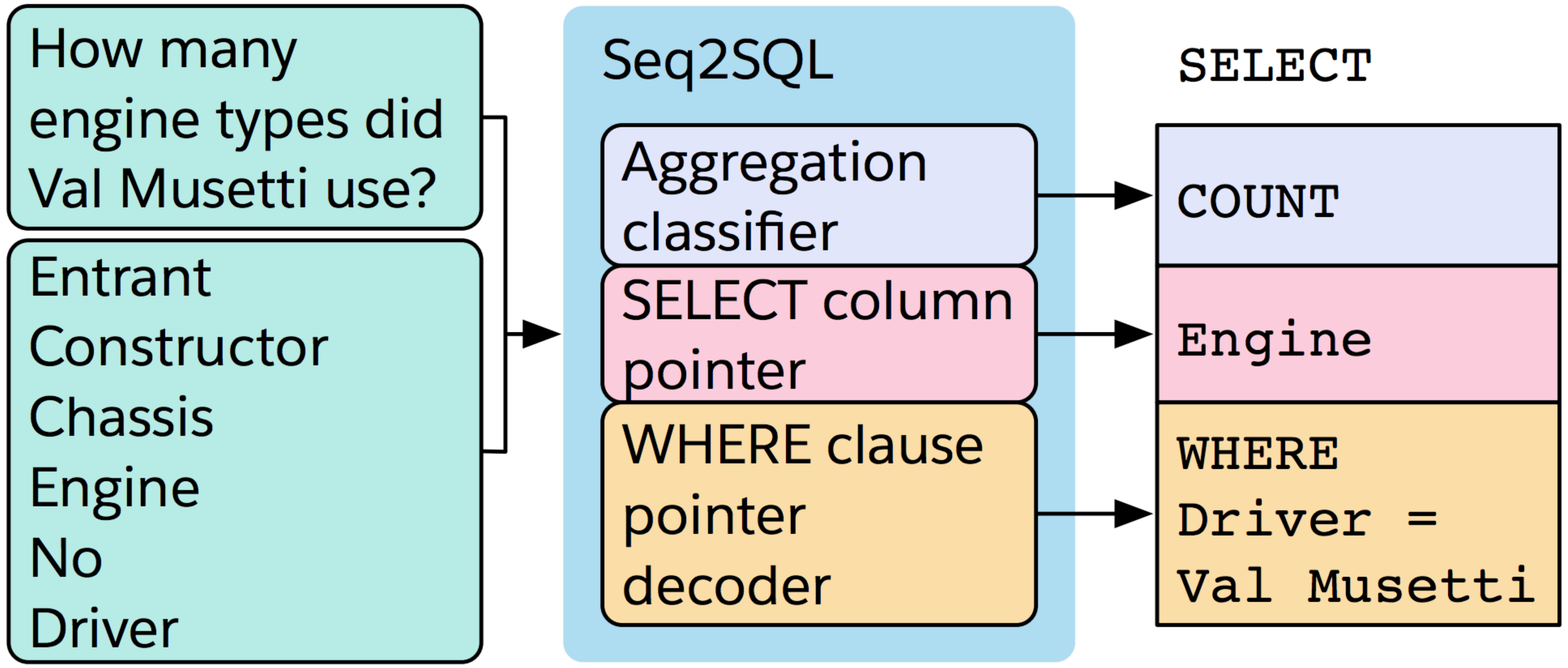

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Attention

Problems with Seq2seq Models

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- Encoder-decoder models like to repeat themselves:

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- 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

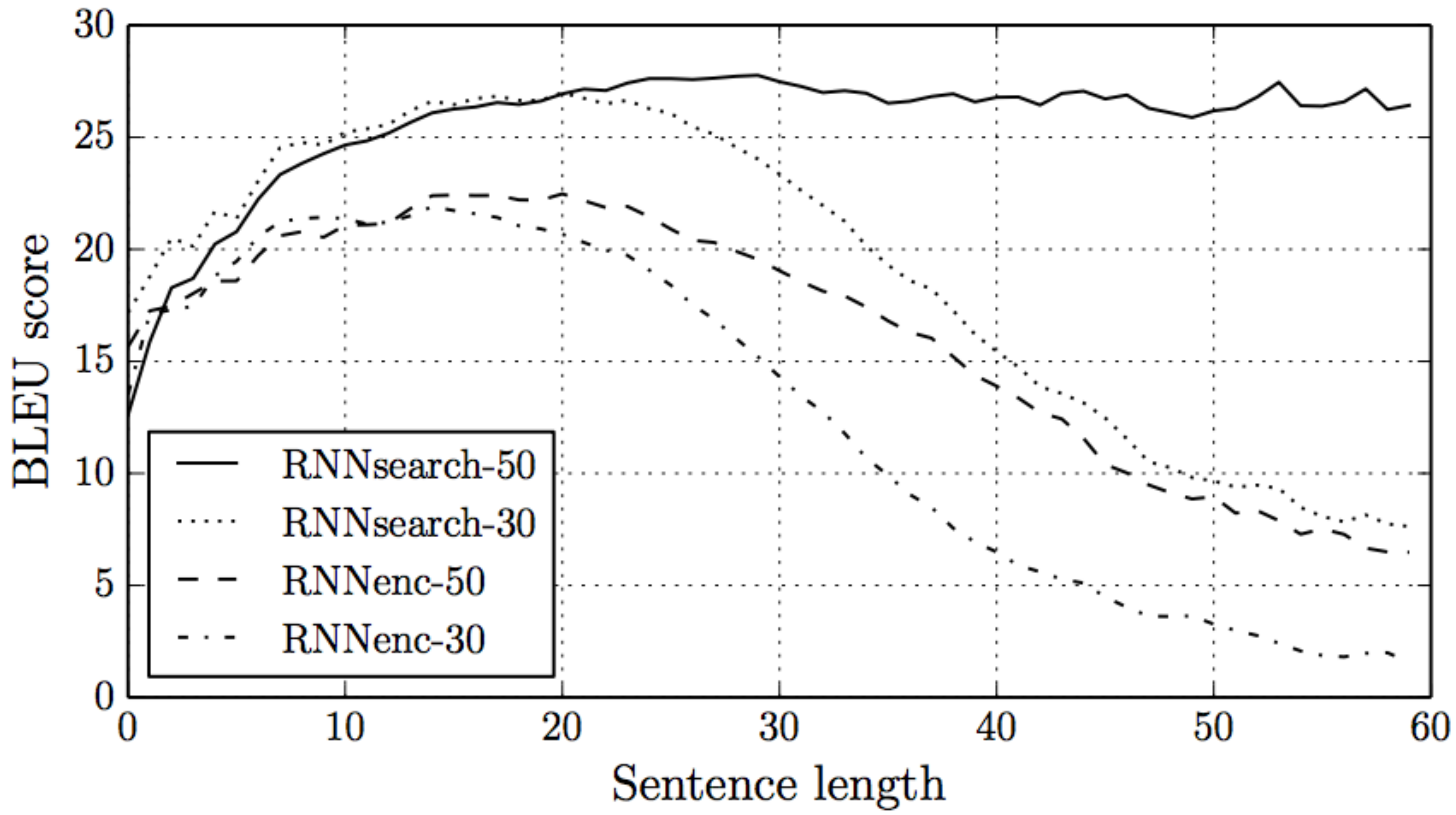
fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] . . . , a été *démonté* jeudi matin

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

Bahdanau et al. (2014)

Aligned Inputs

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

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the movie was great

le film était bon

Aligned Inputs

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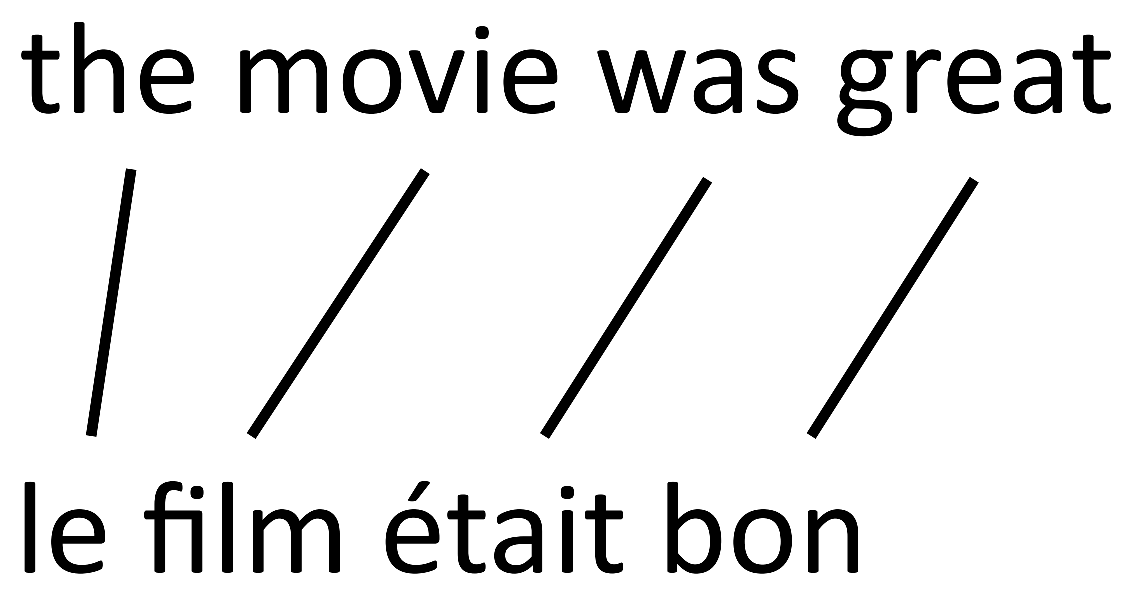

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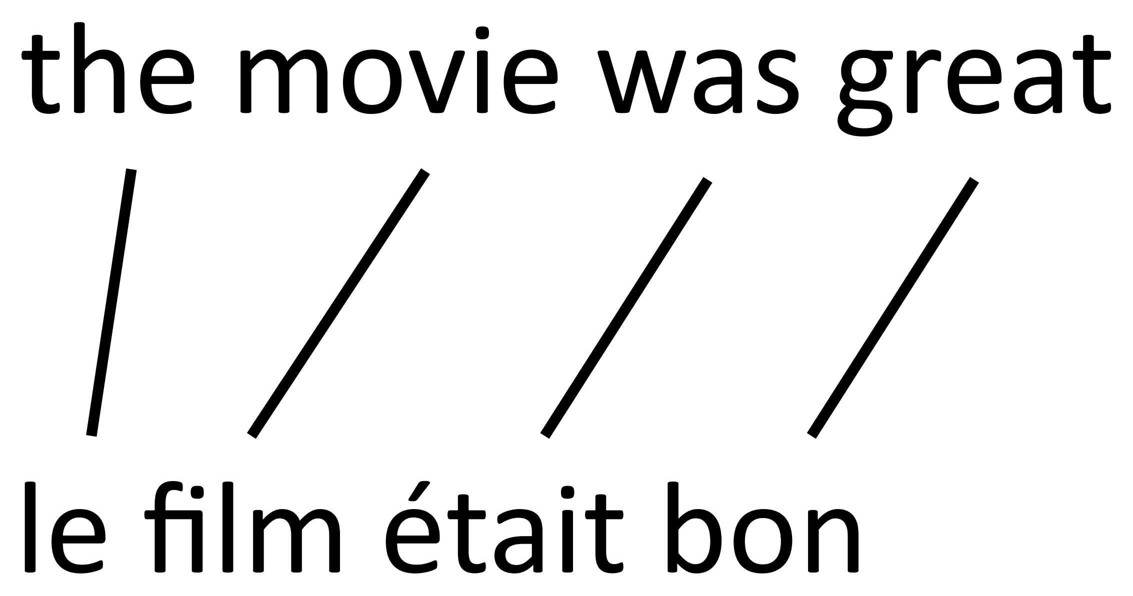

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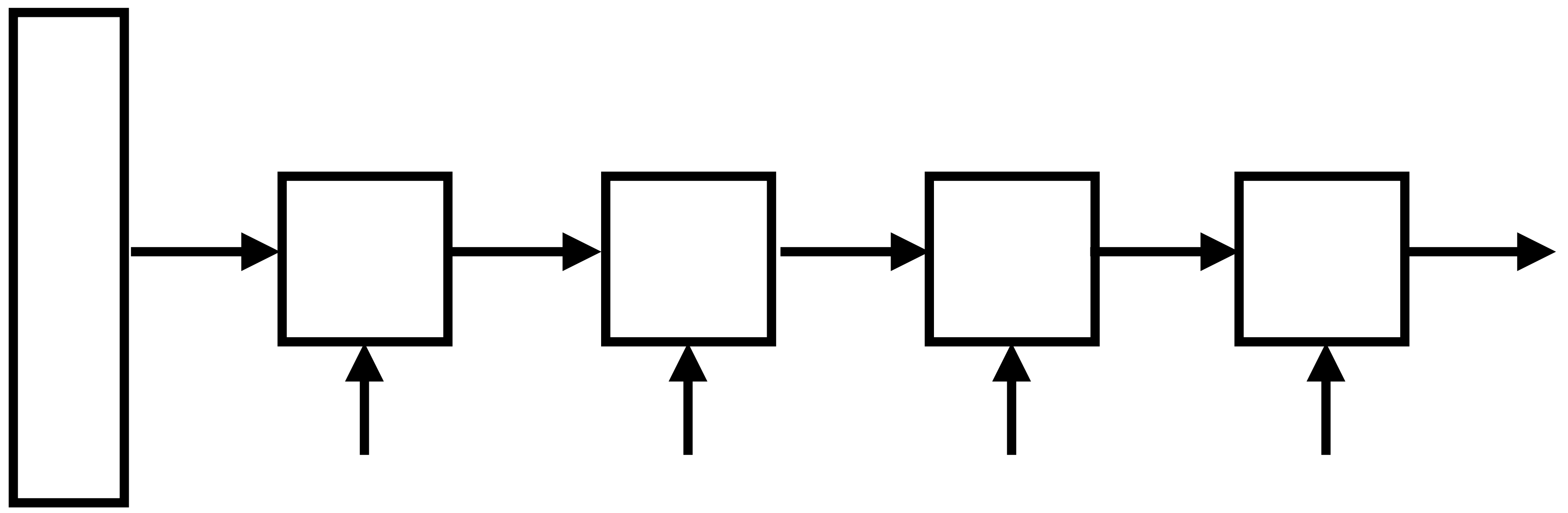

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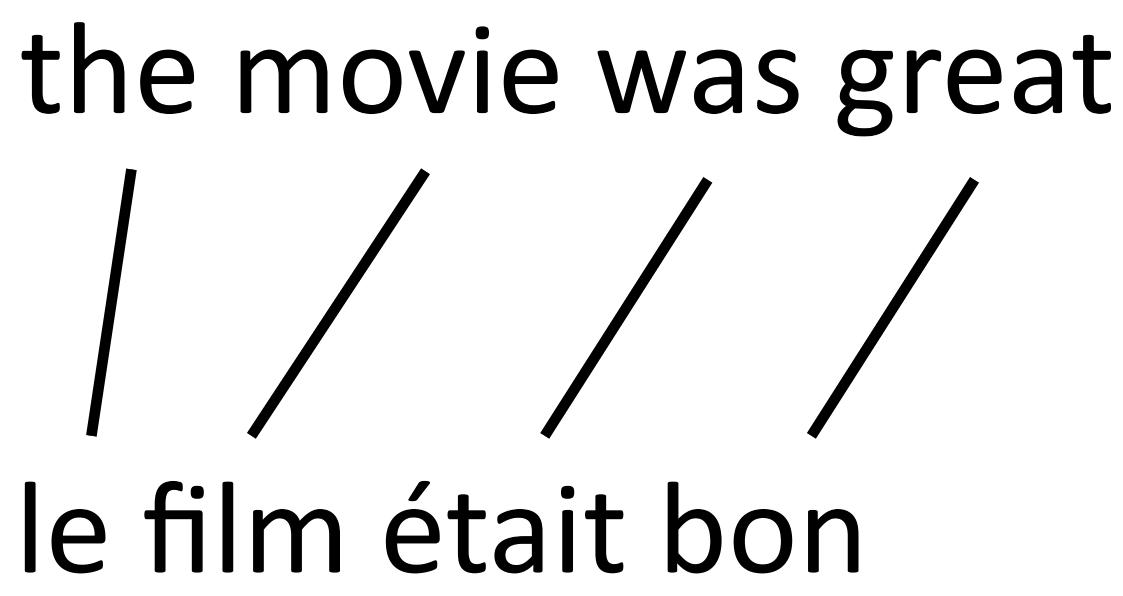

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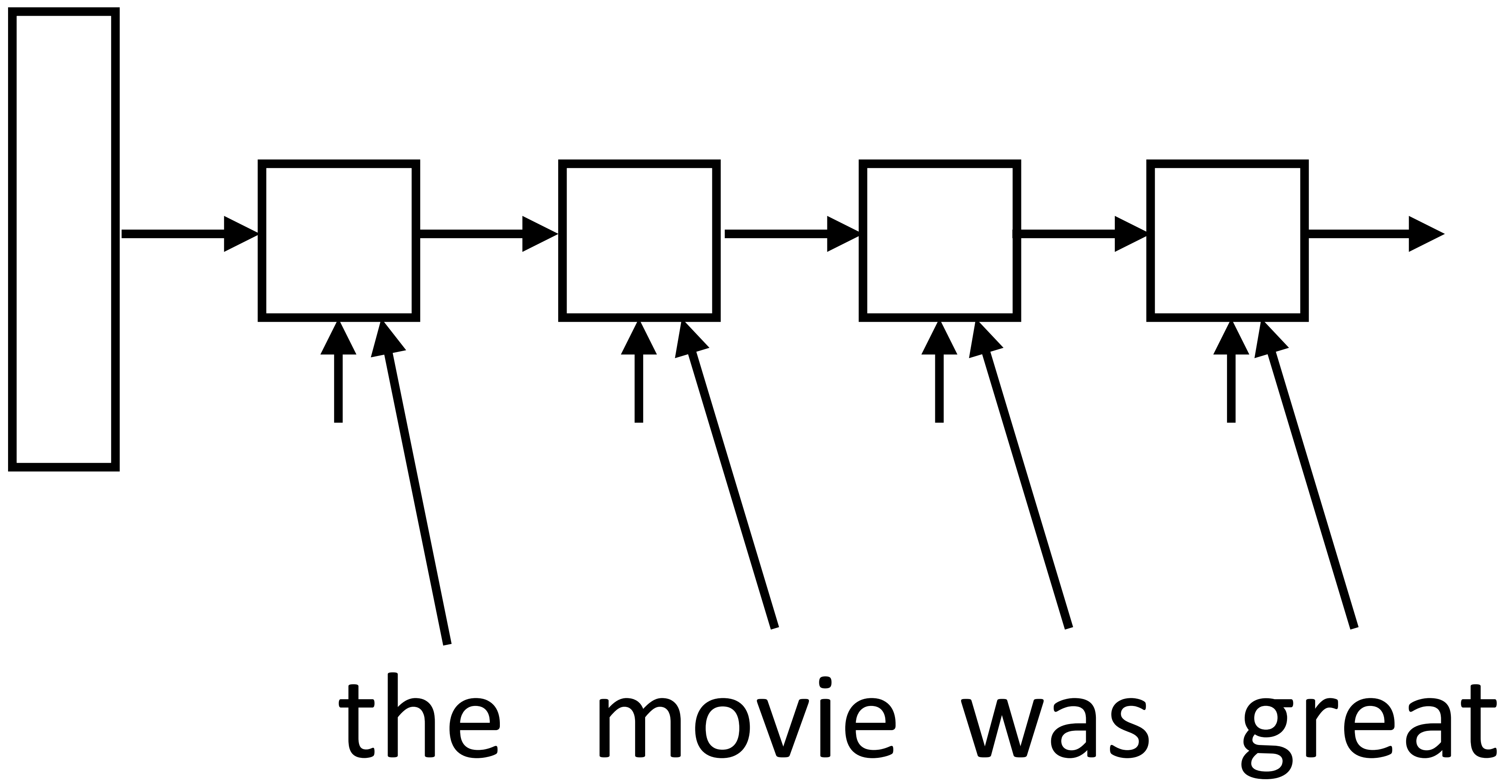

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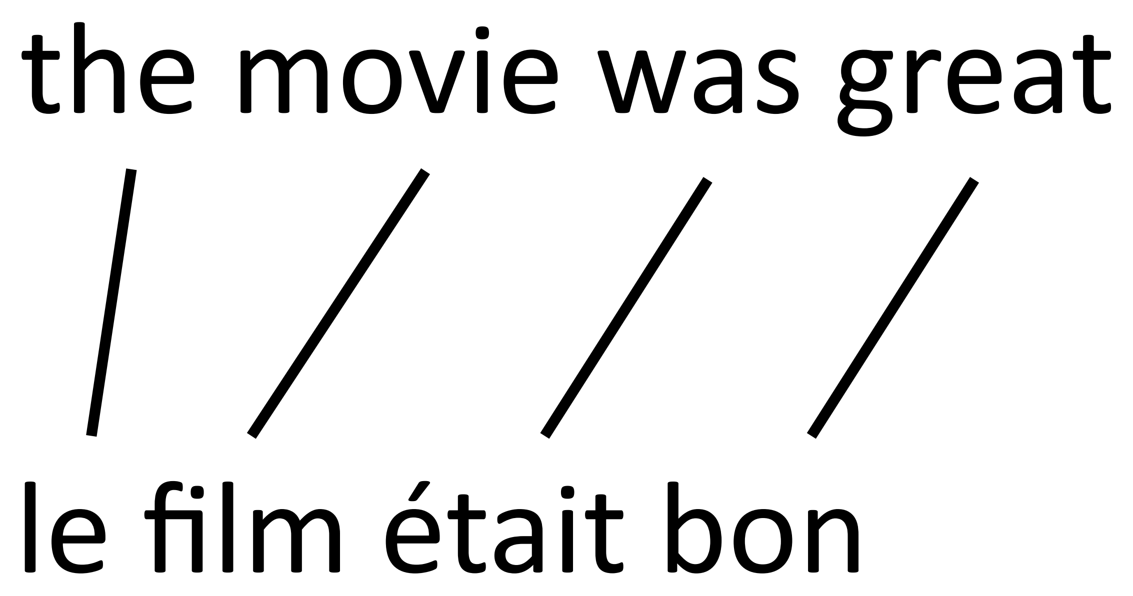

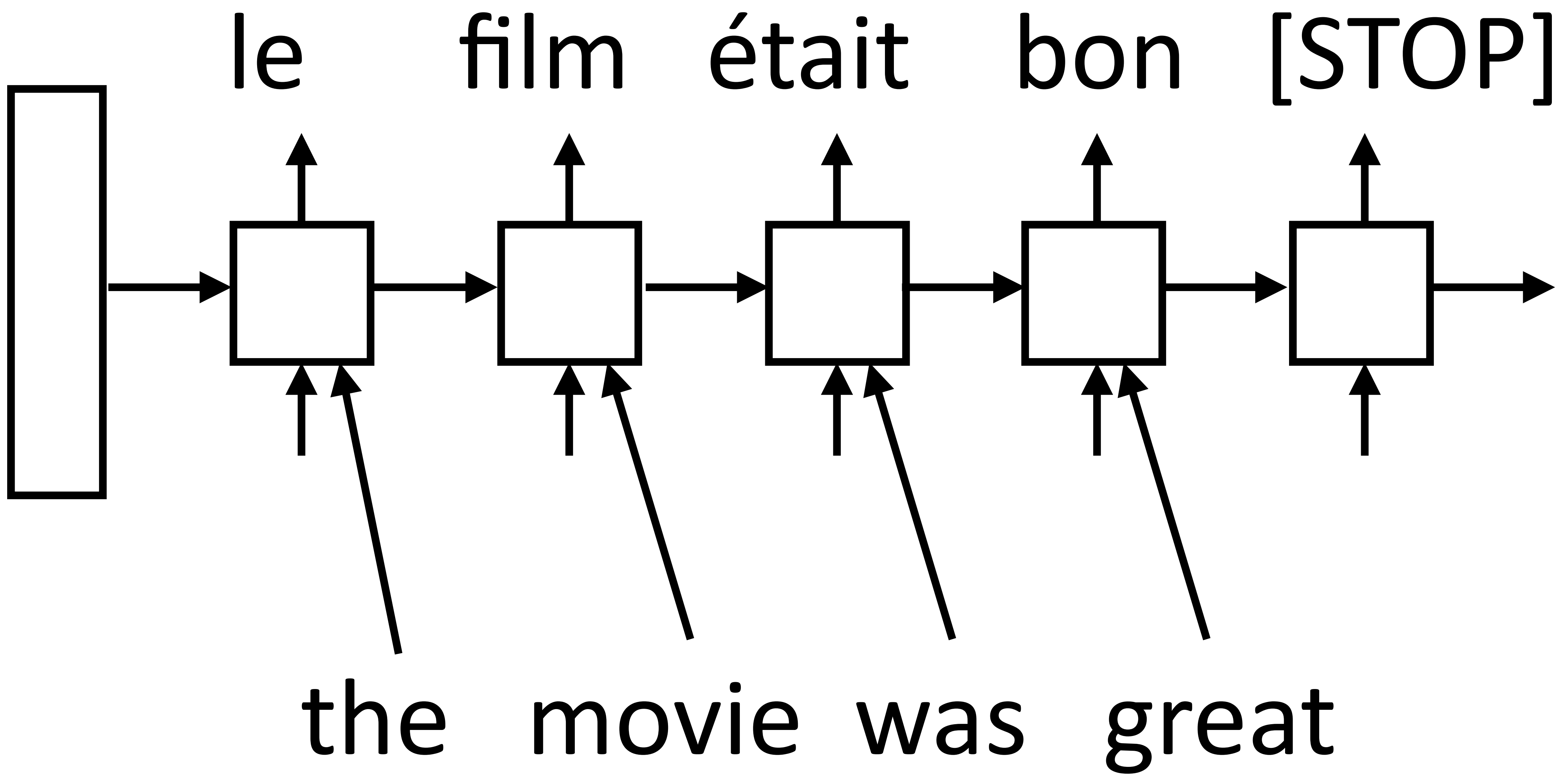

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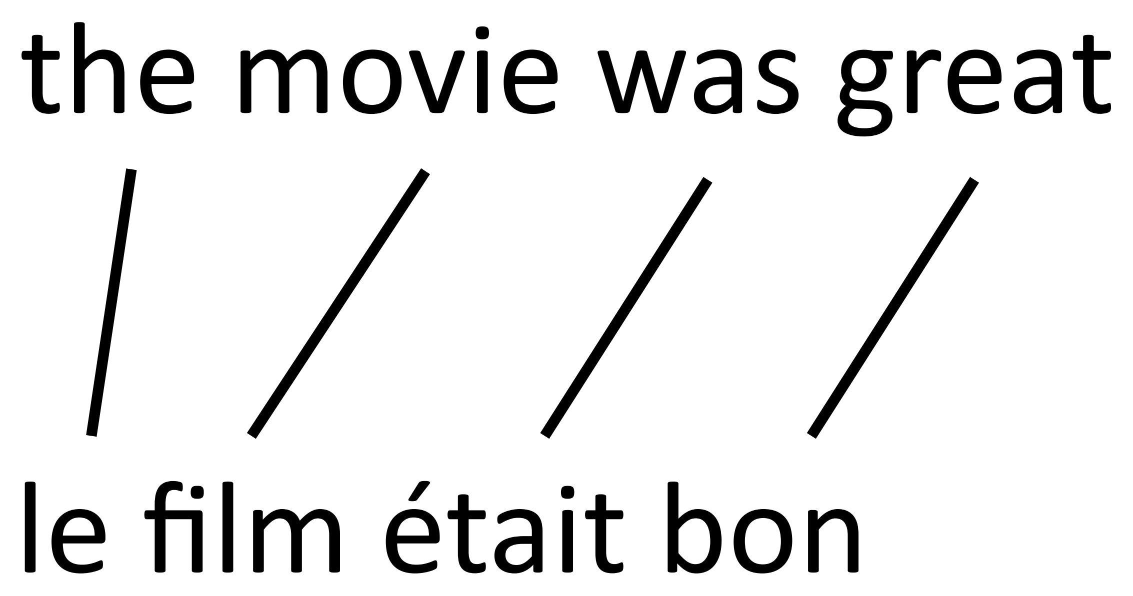
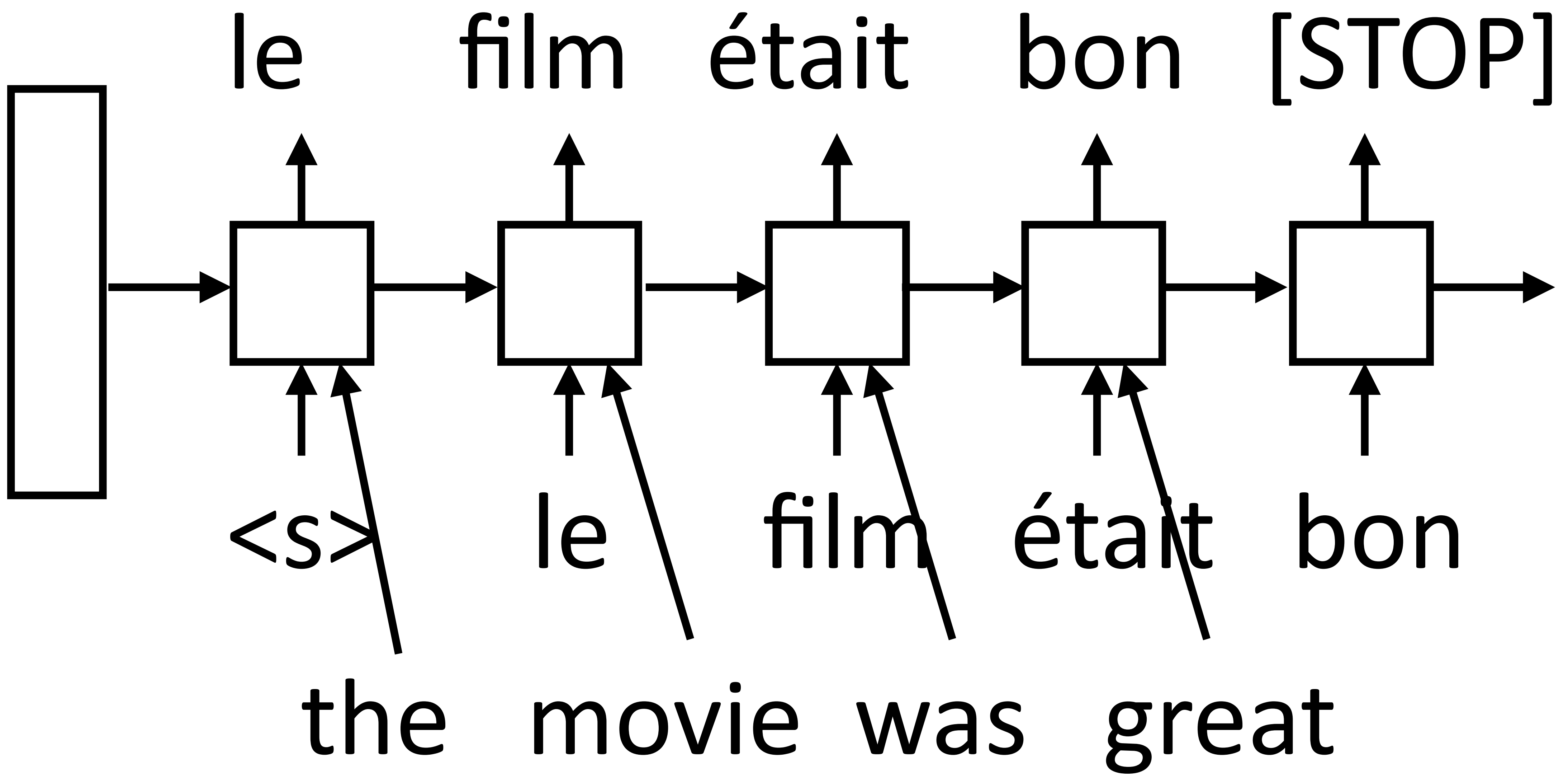
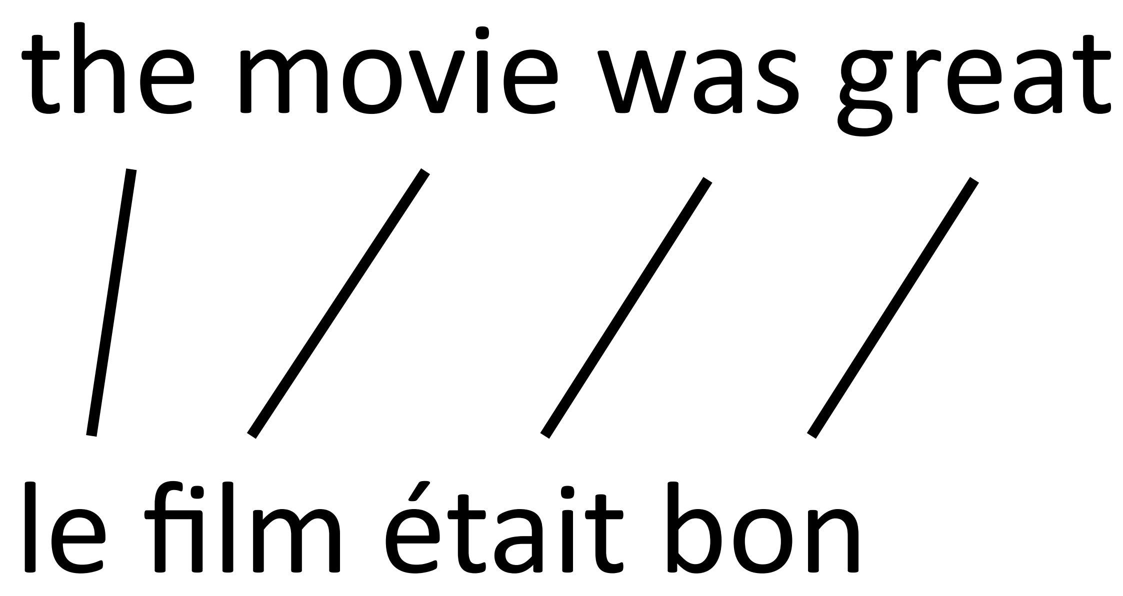
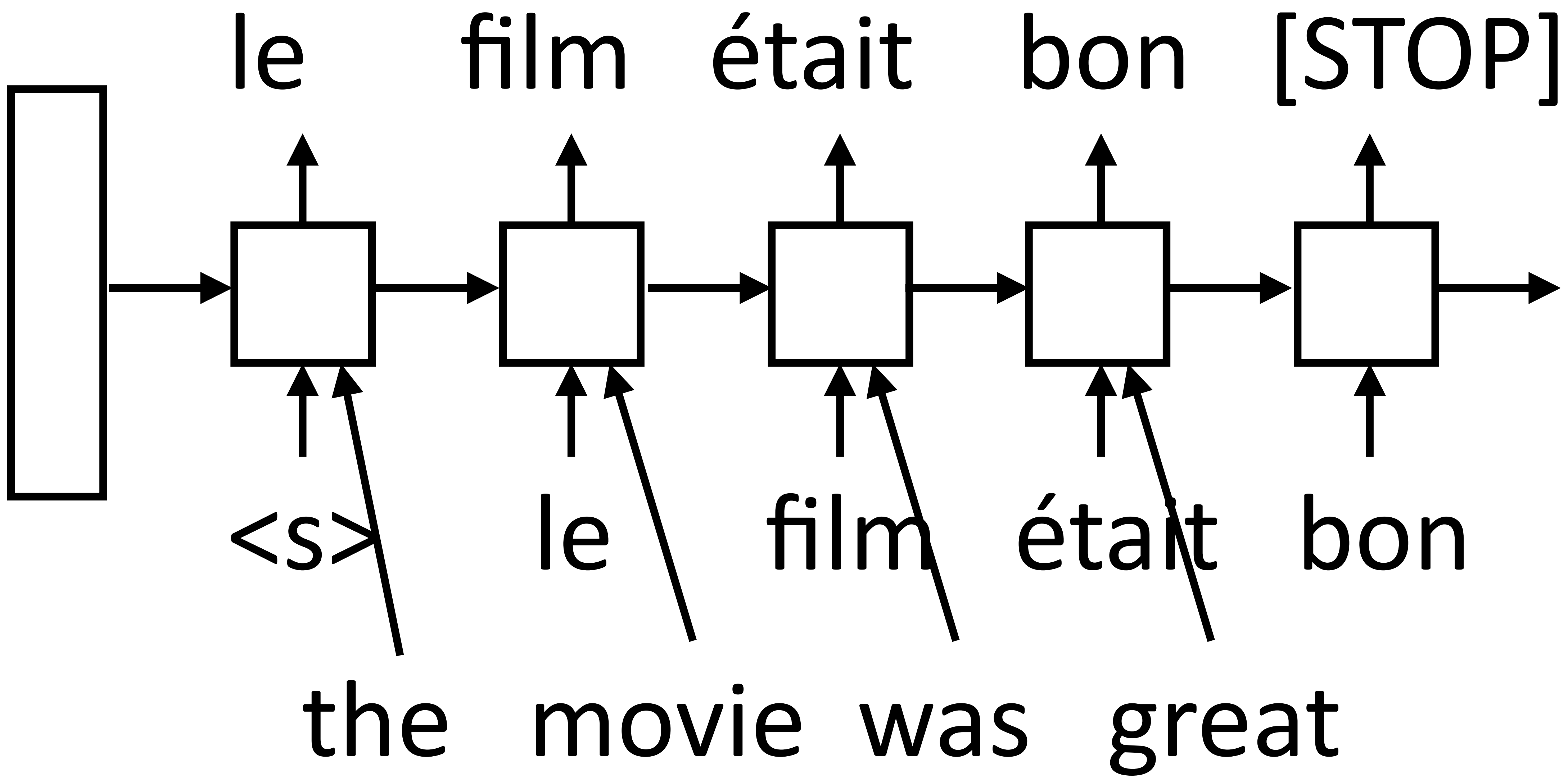




Aligned Inputs

- Suppose we knew the source and target would be word-by-word translated
- Can look at the corresponding input word when translating — this could scale!
- Much less burden on the hidden state





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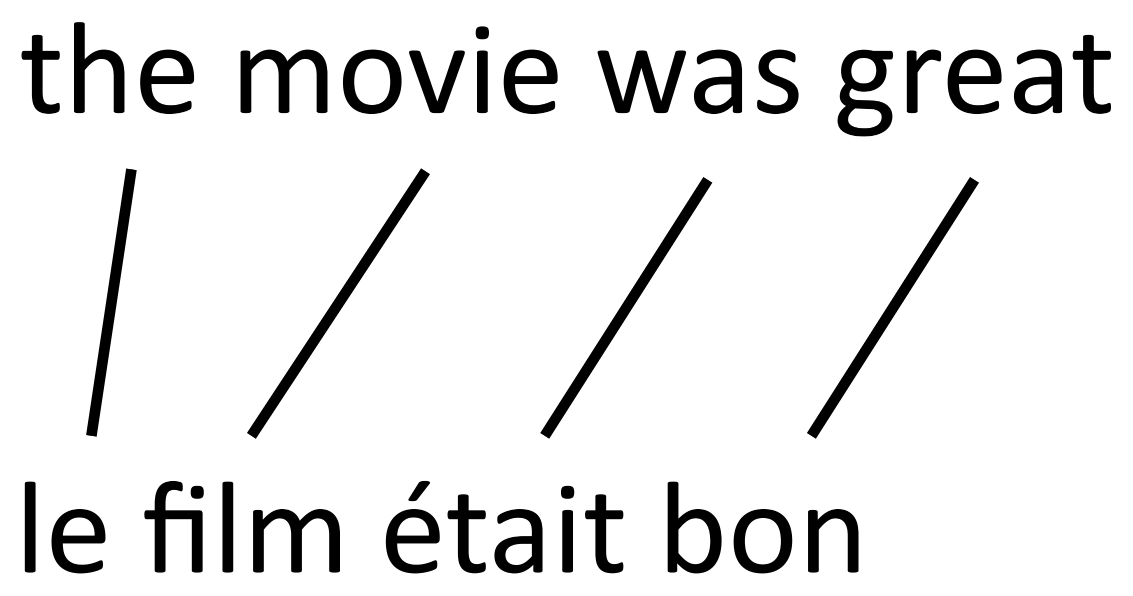

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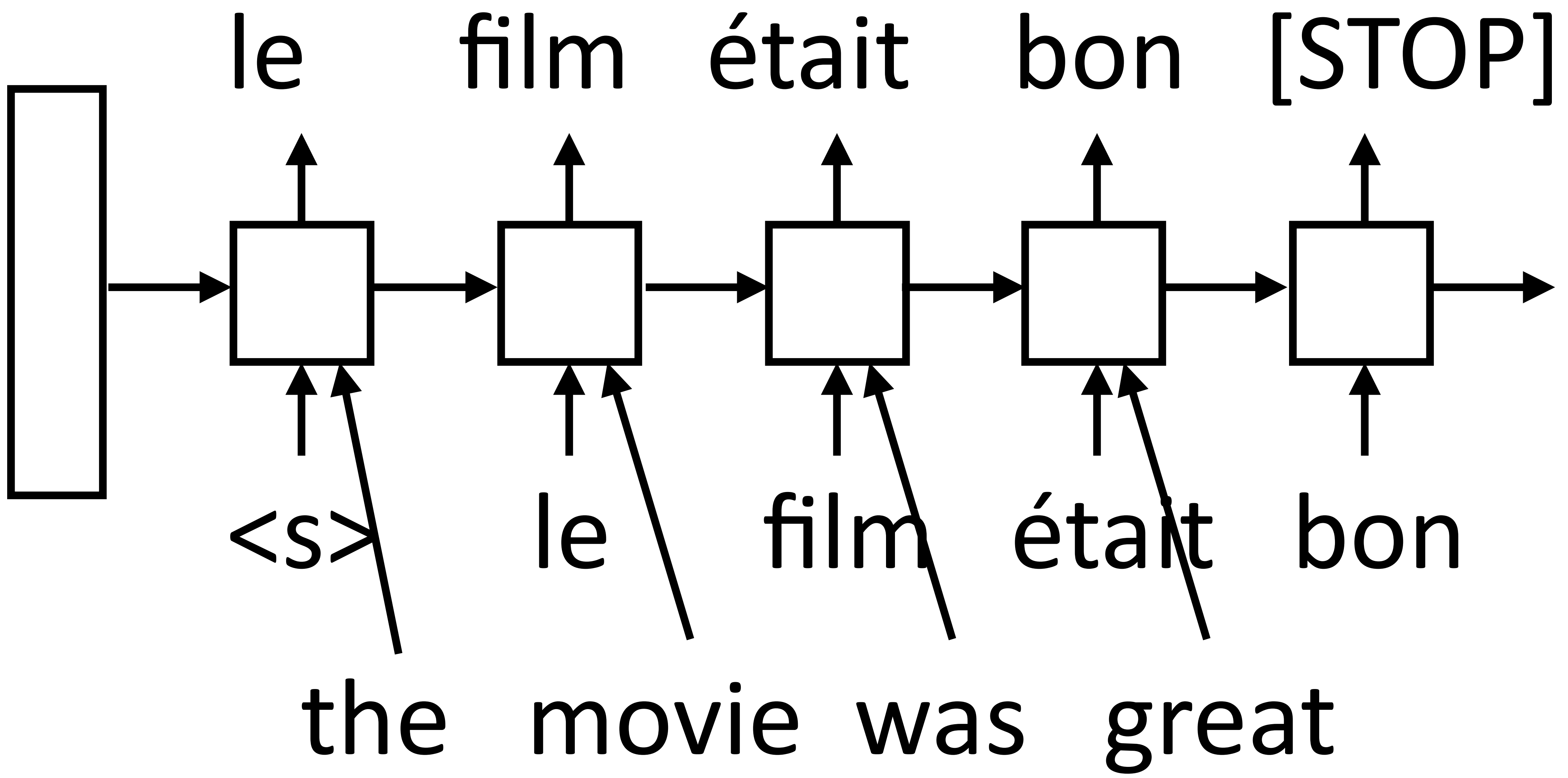
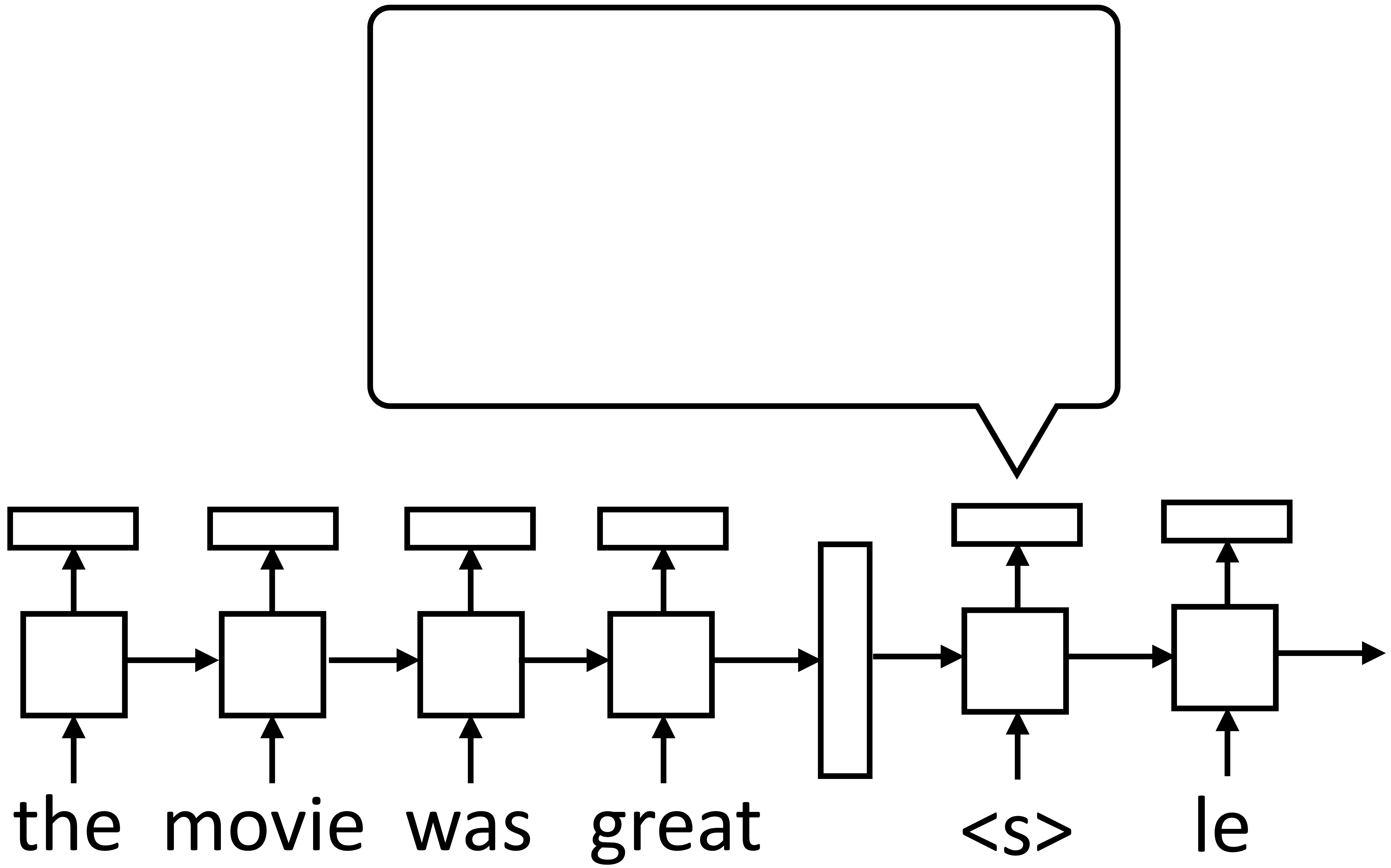


- Much less burden on the hidden state

- How can we achieve this without hardcoding it?

Attention



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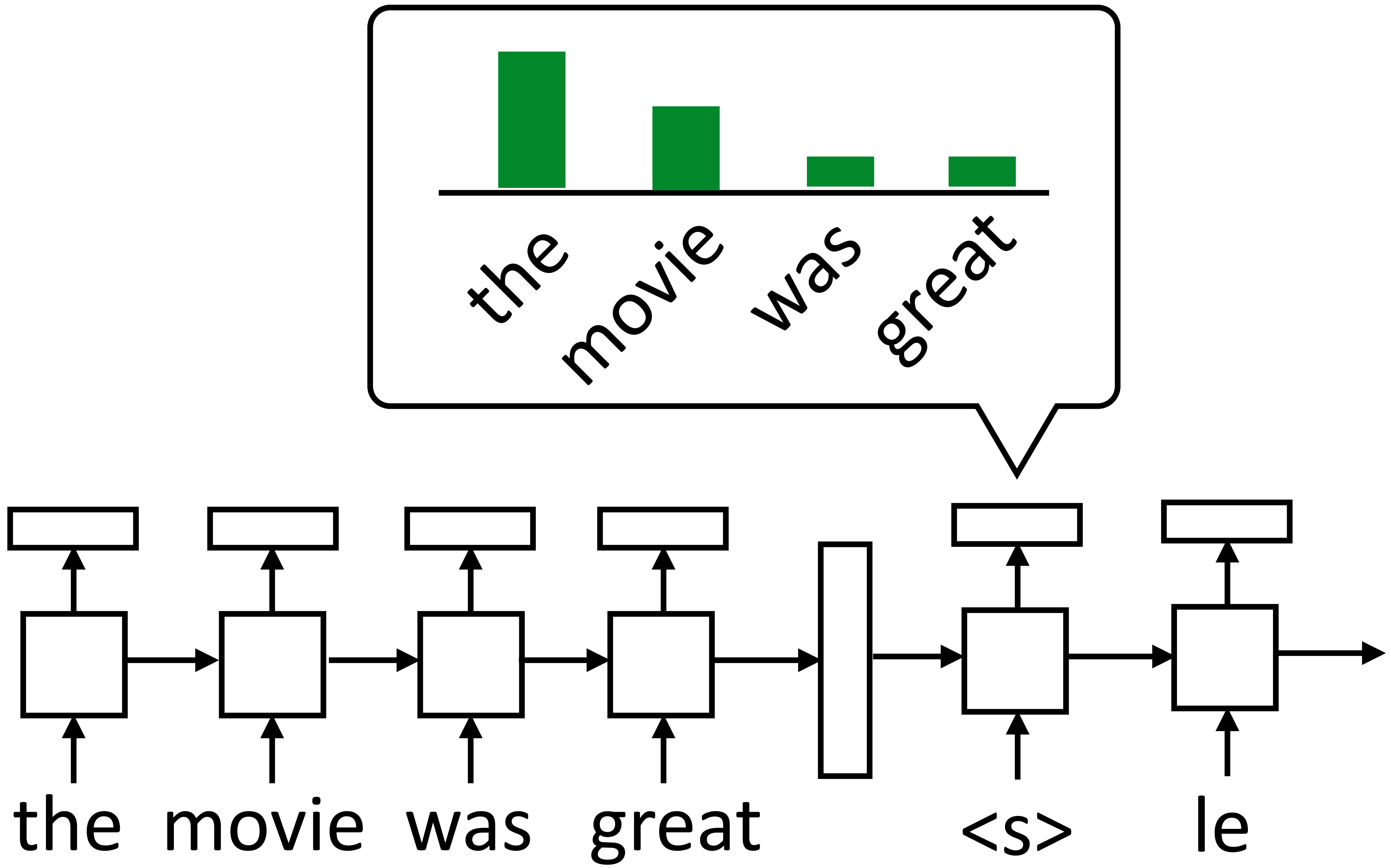

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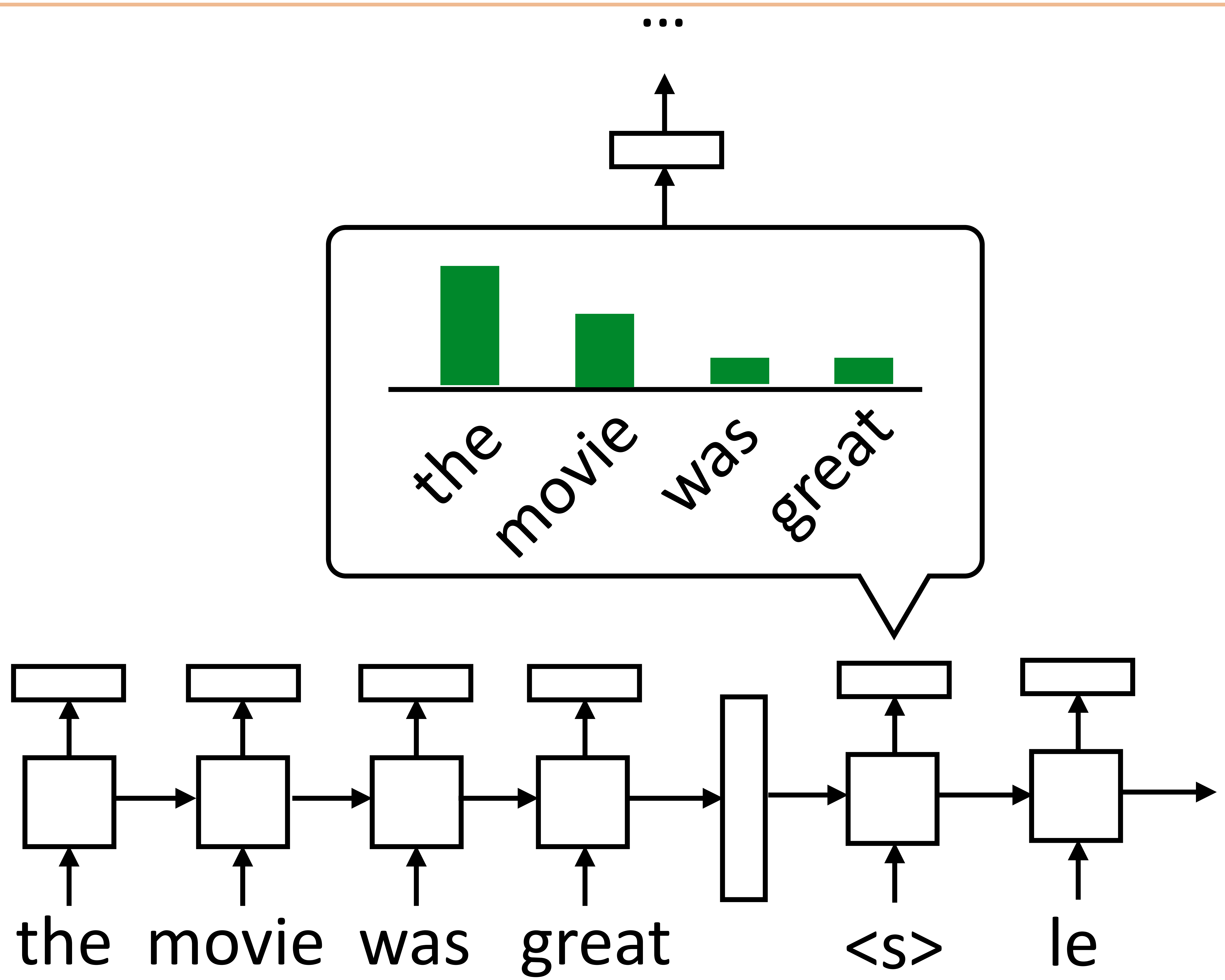

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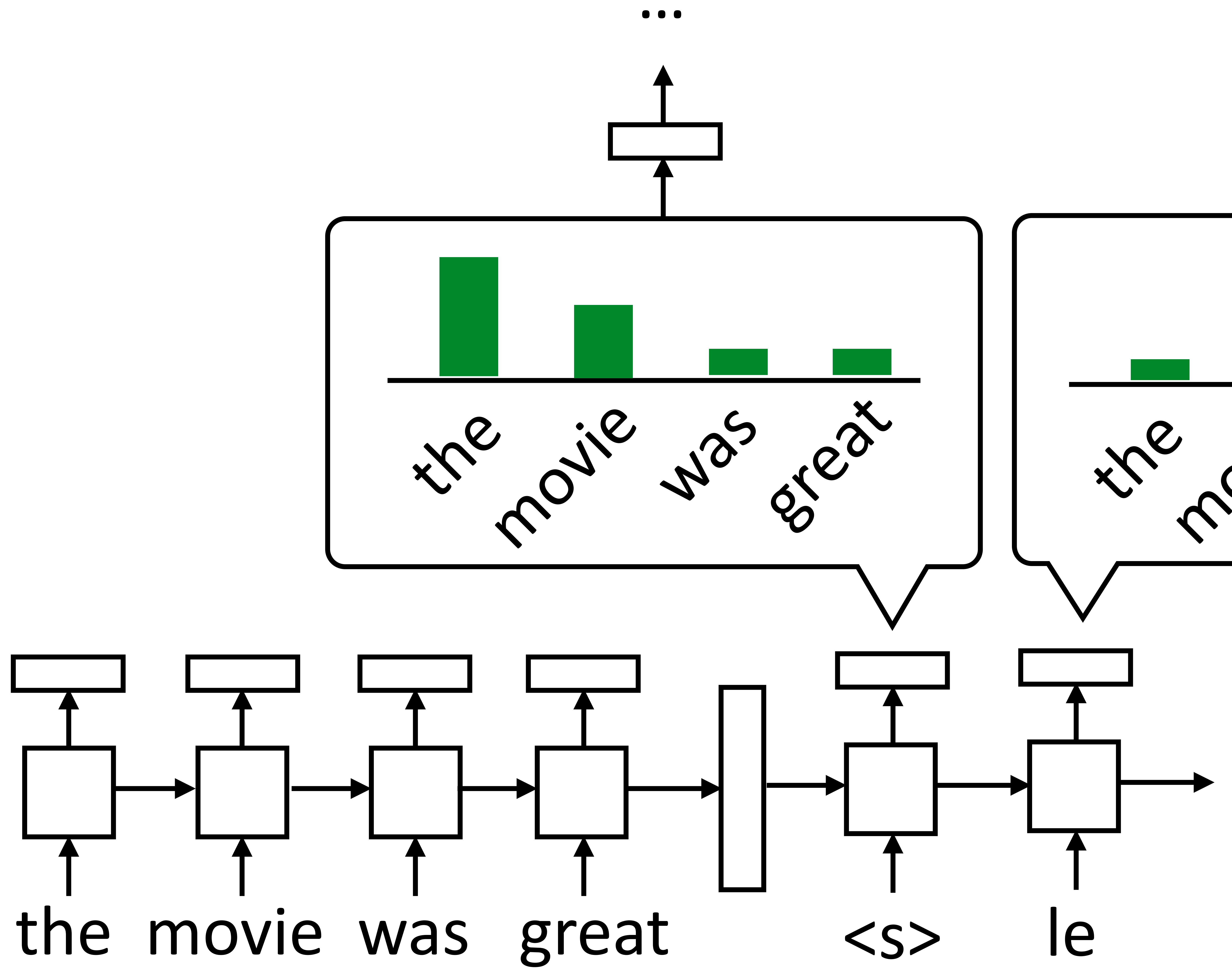
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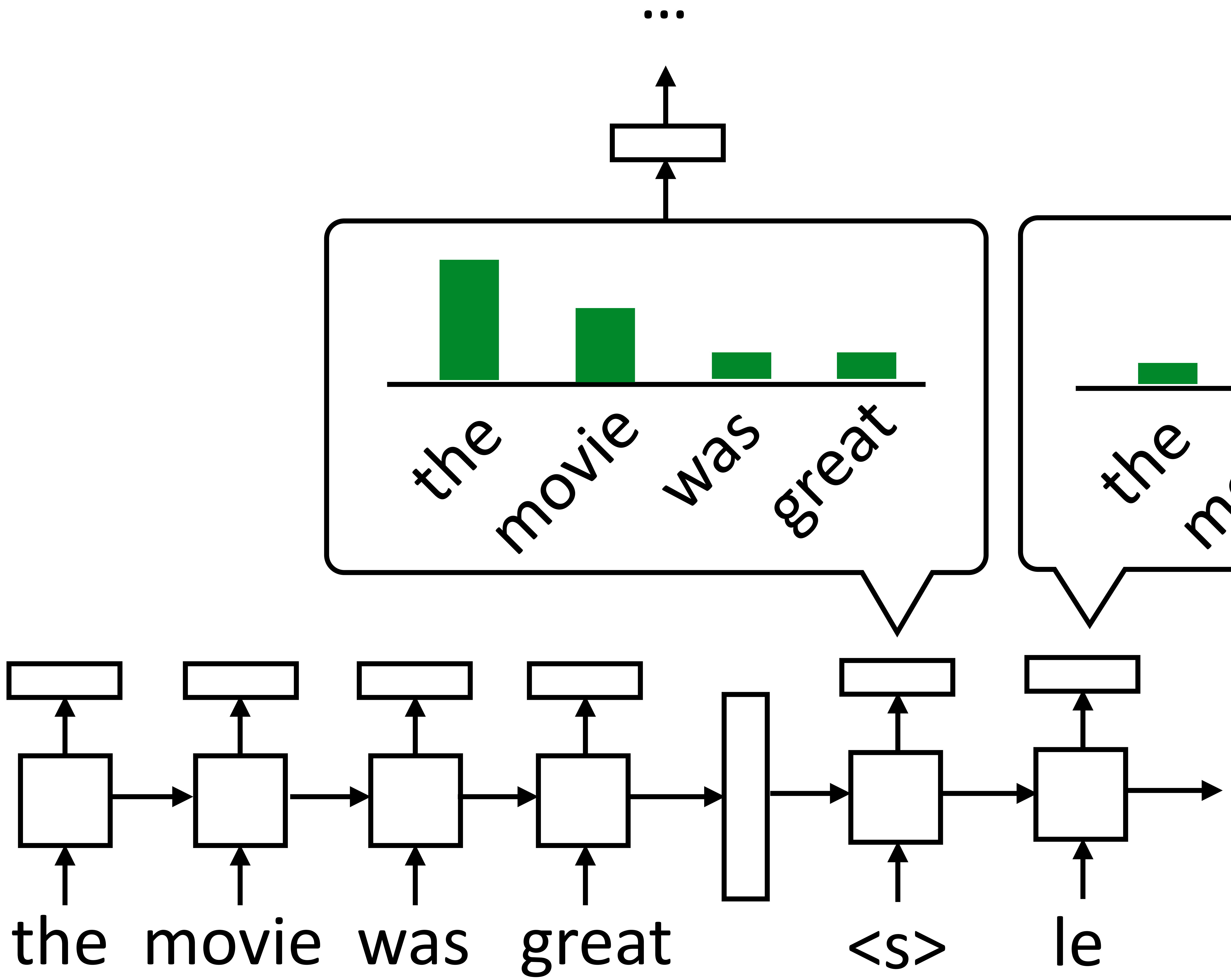

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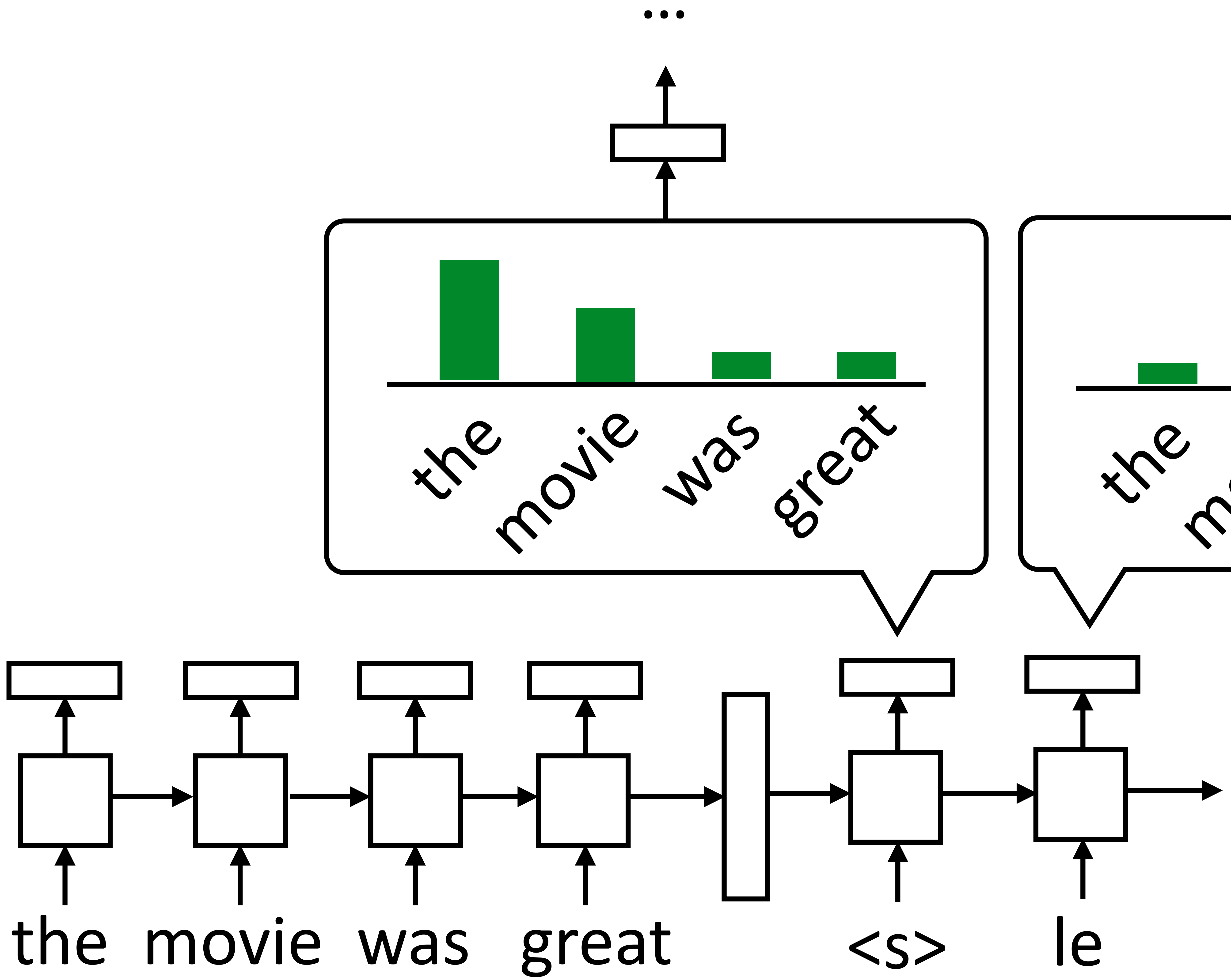

- At each decoder state, compute a distribution over source inputs based on current decoder state

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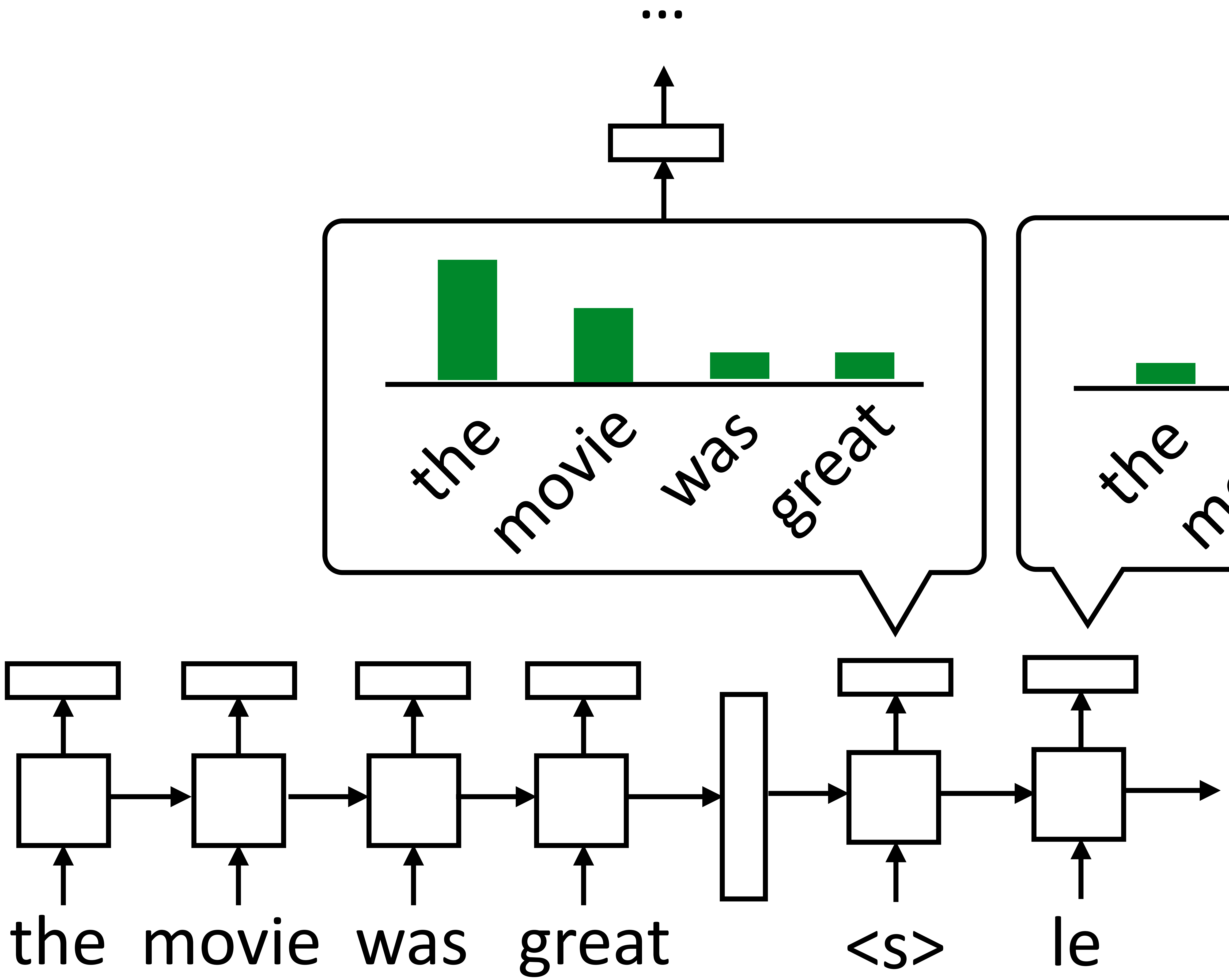
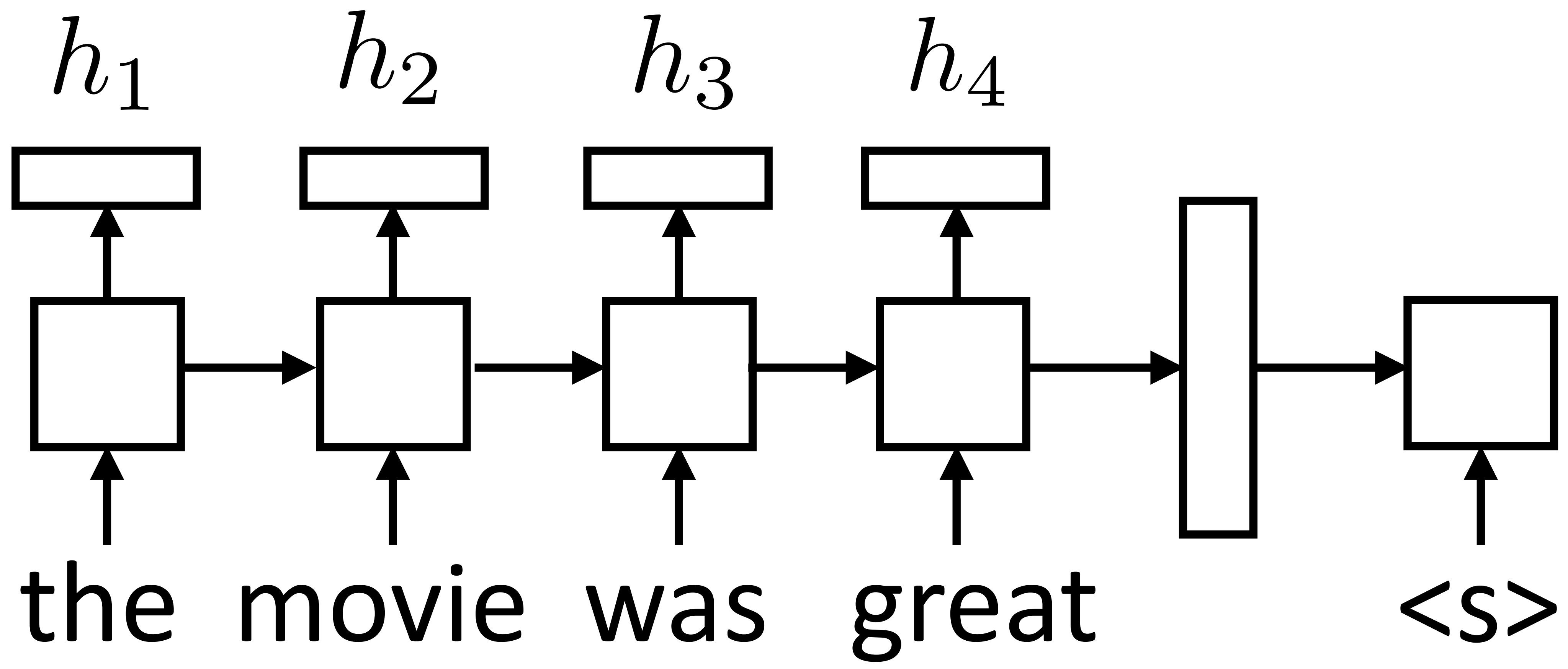


- At each decoder state, compute a distribution over source inputs based on current decoder state
- Use that in output layer

Attention

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



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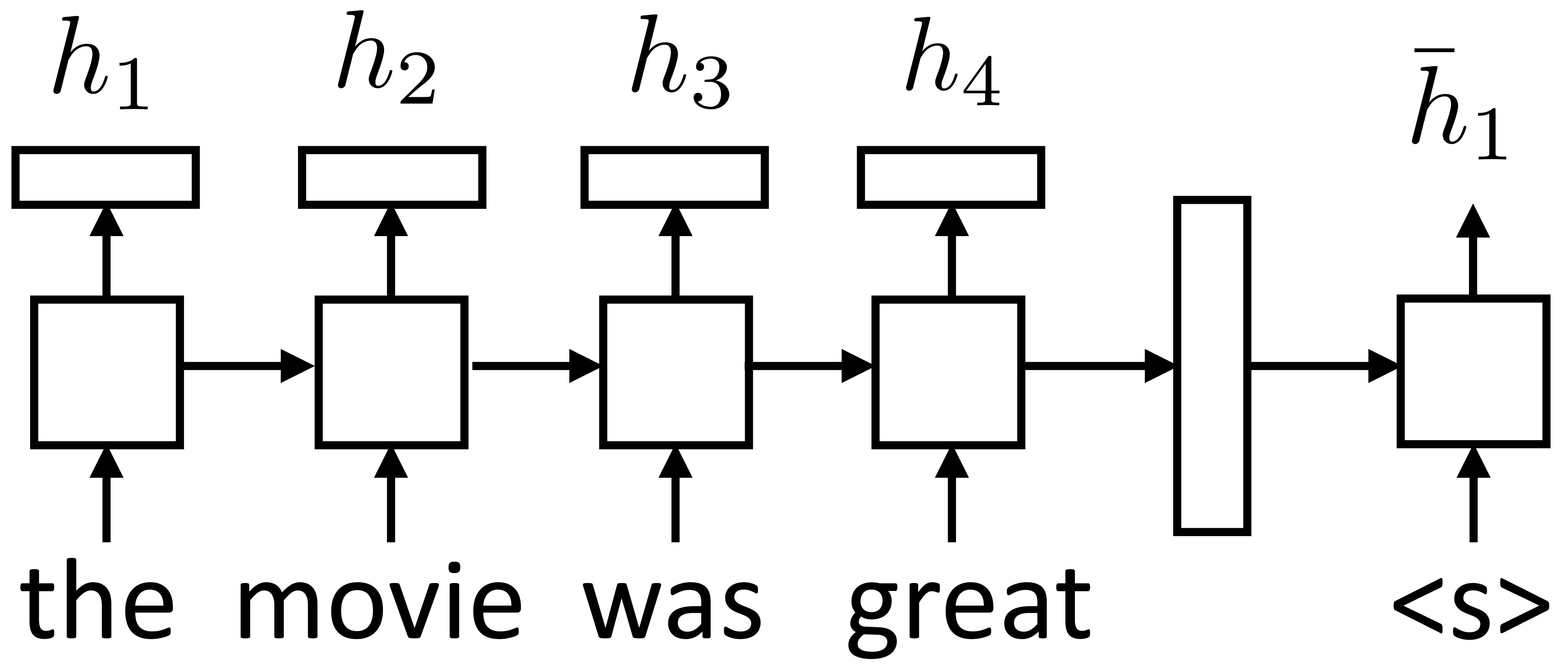

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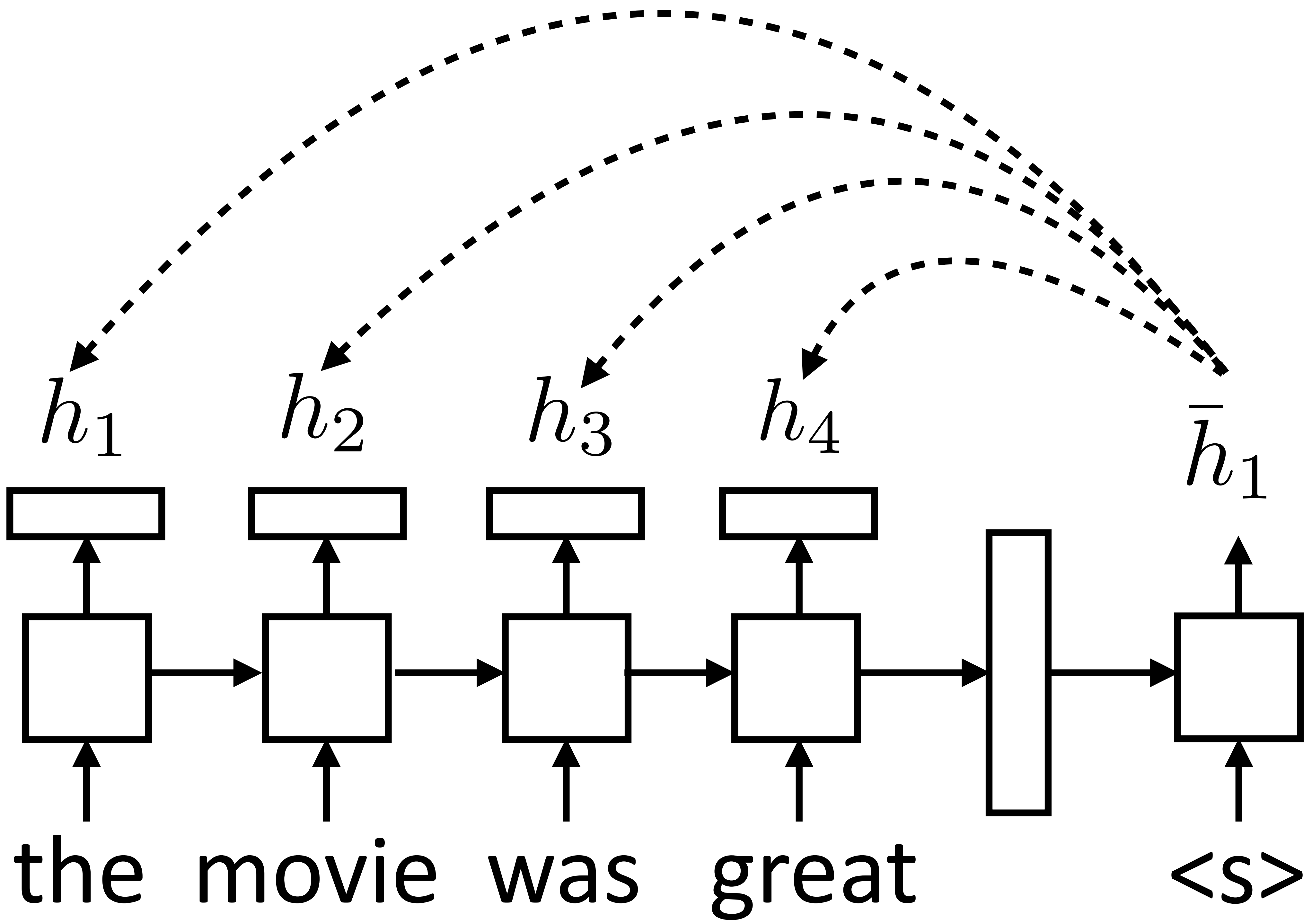

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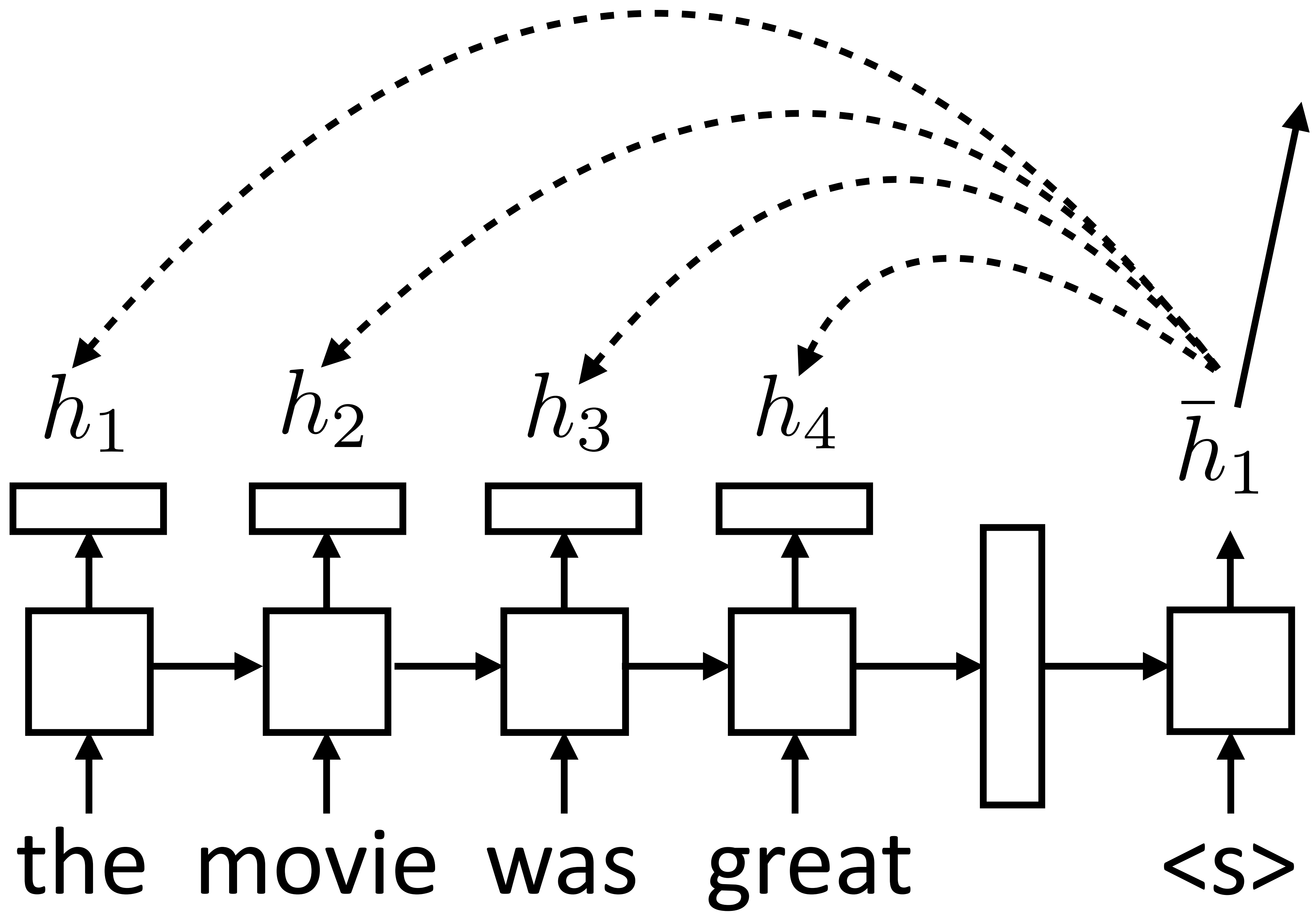

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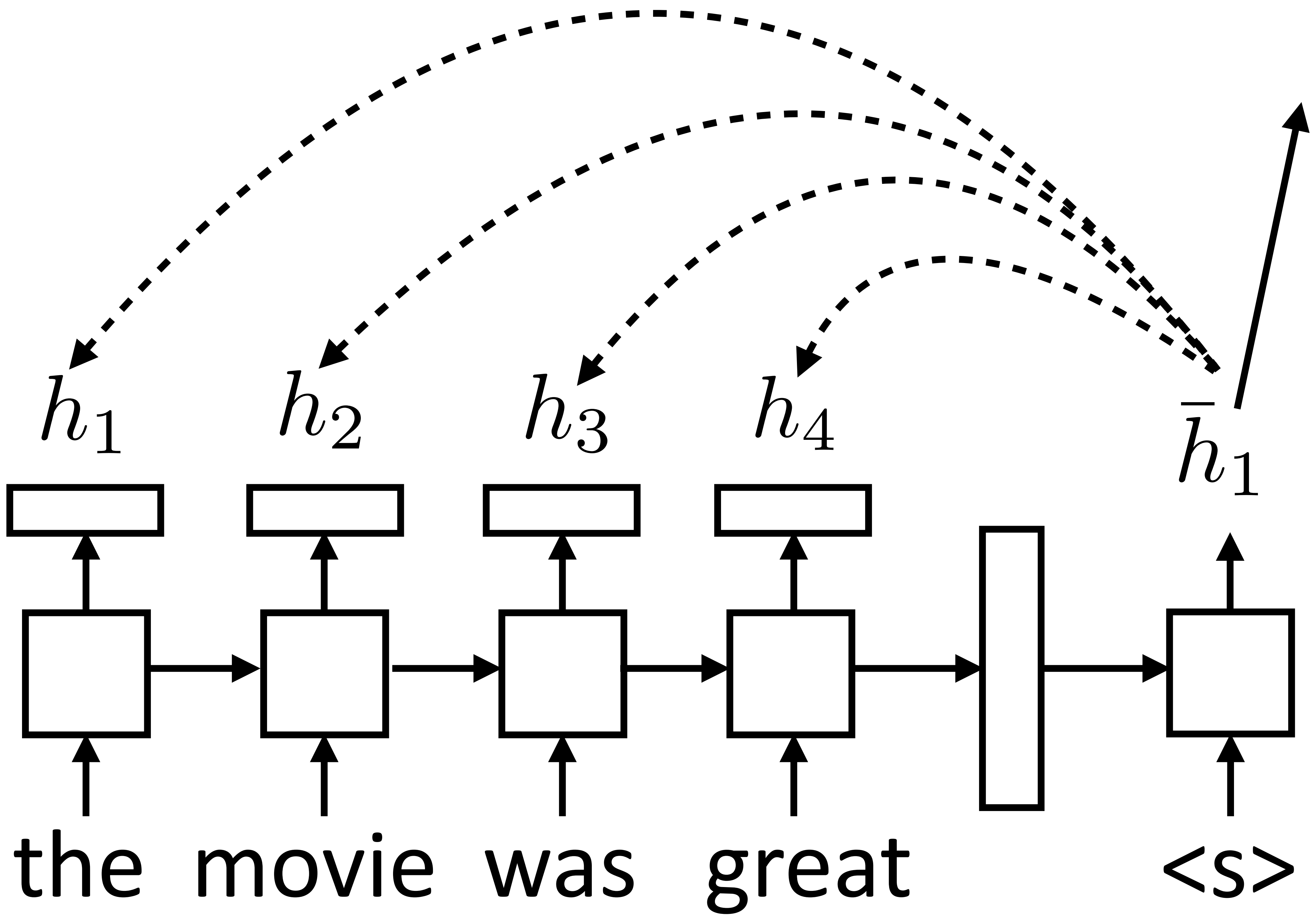

$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

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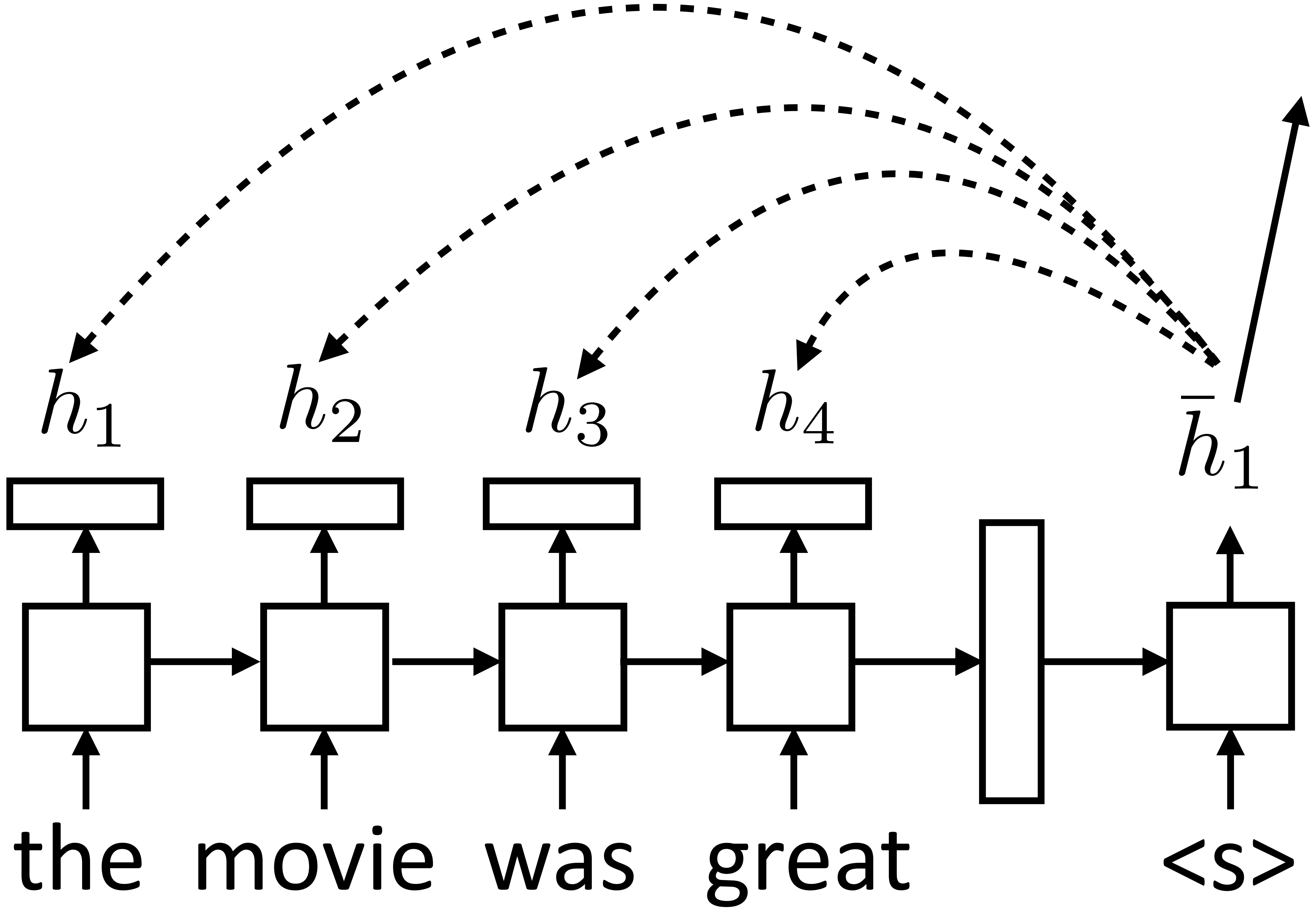
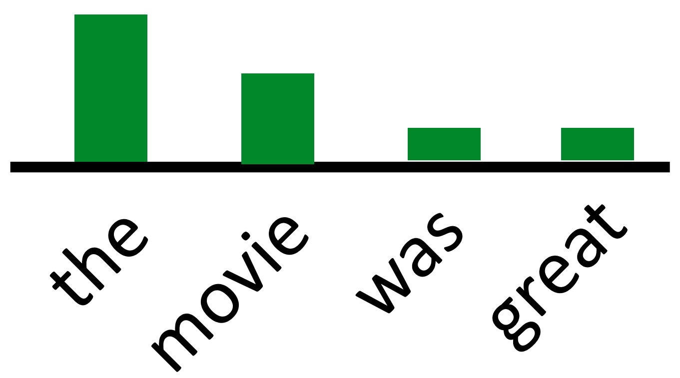


$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$



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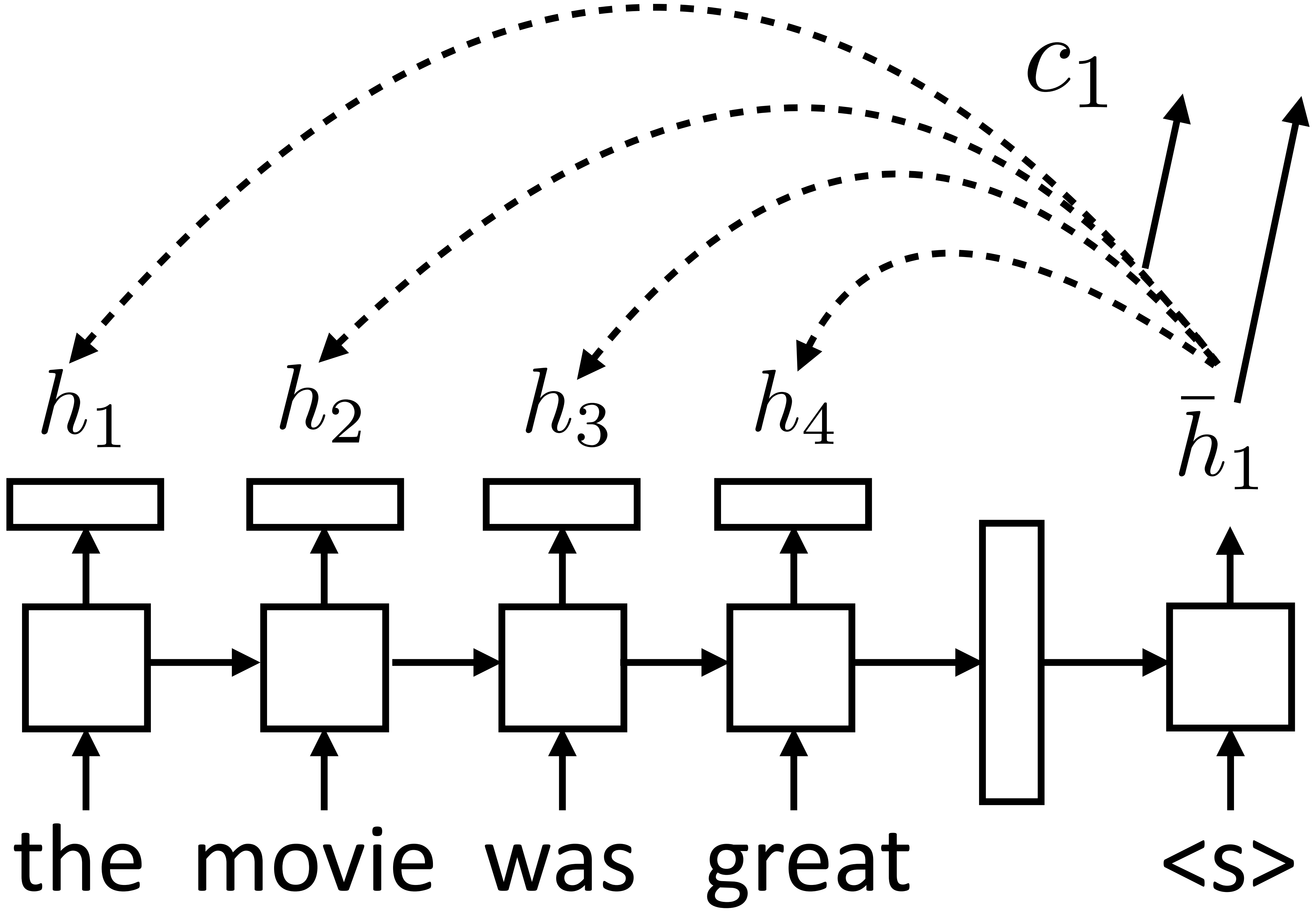

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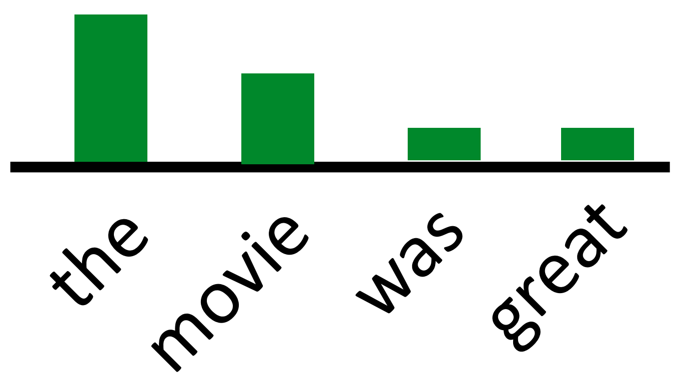

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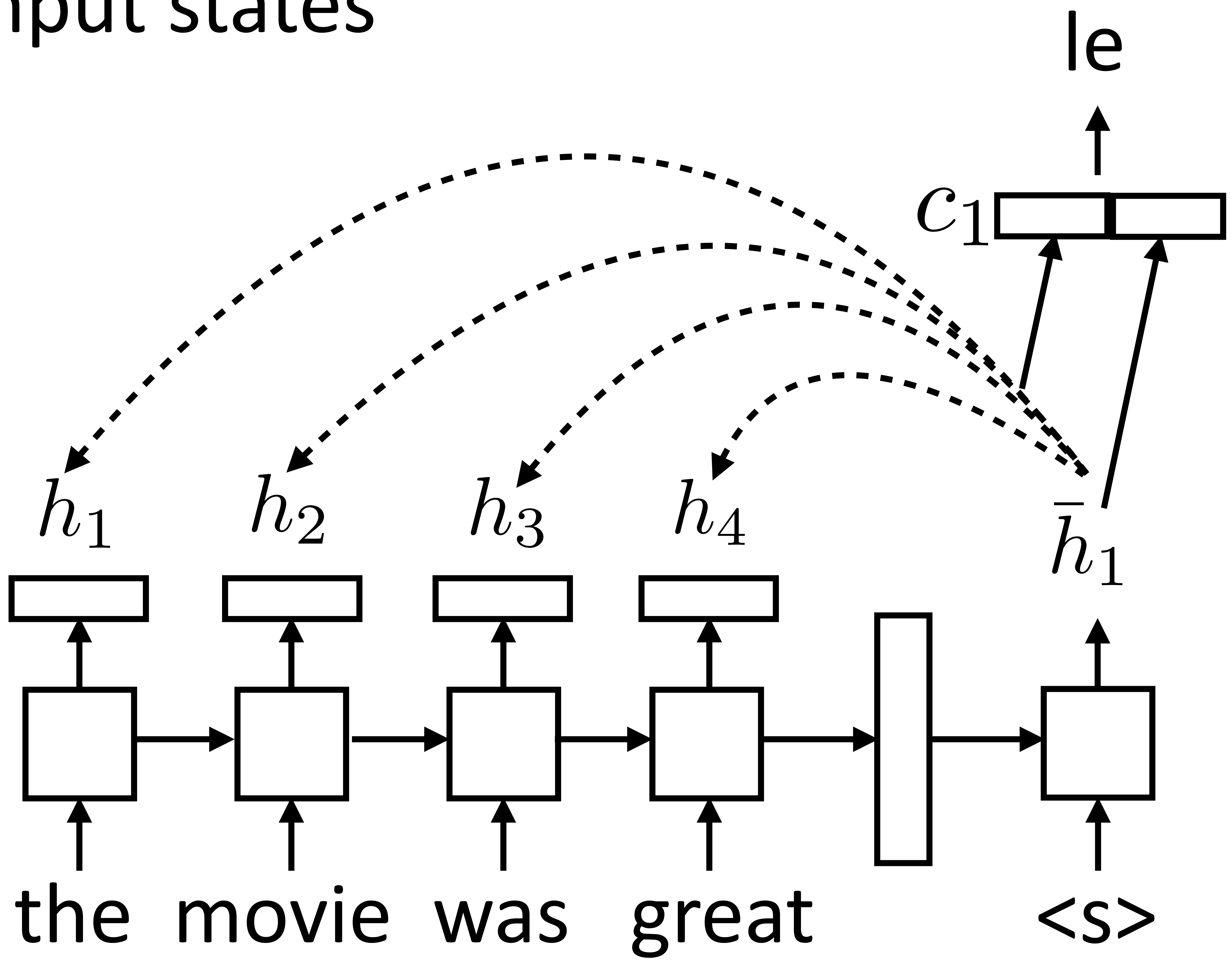

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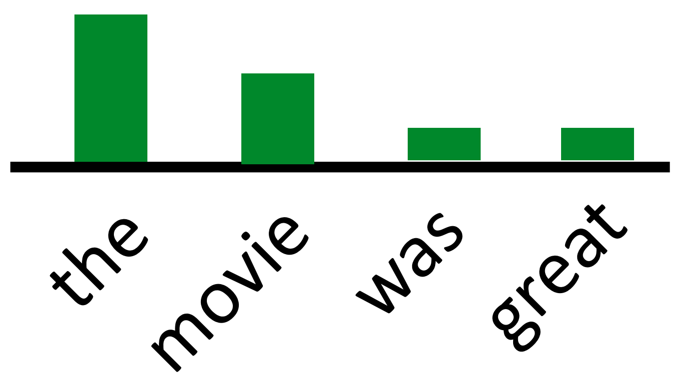

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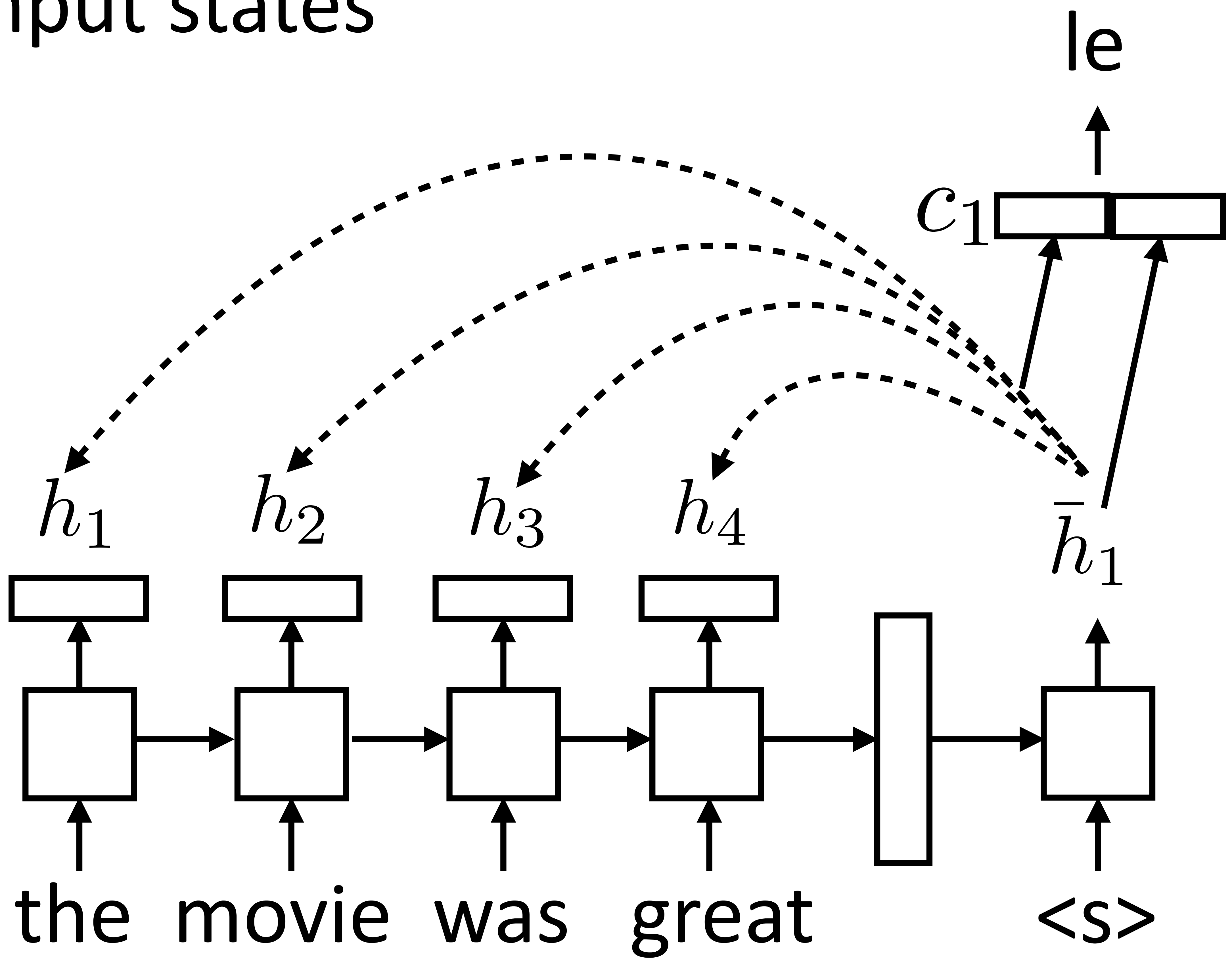

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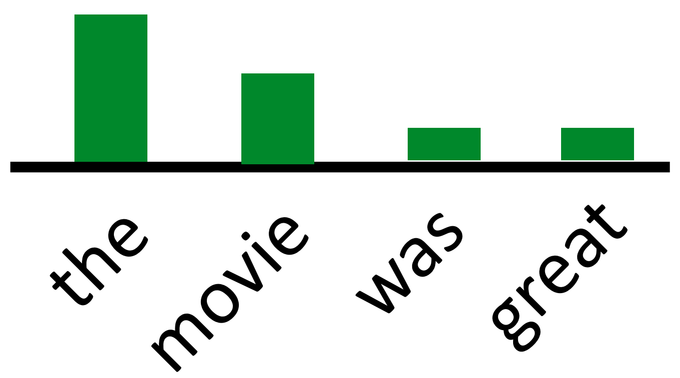

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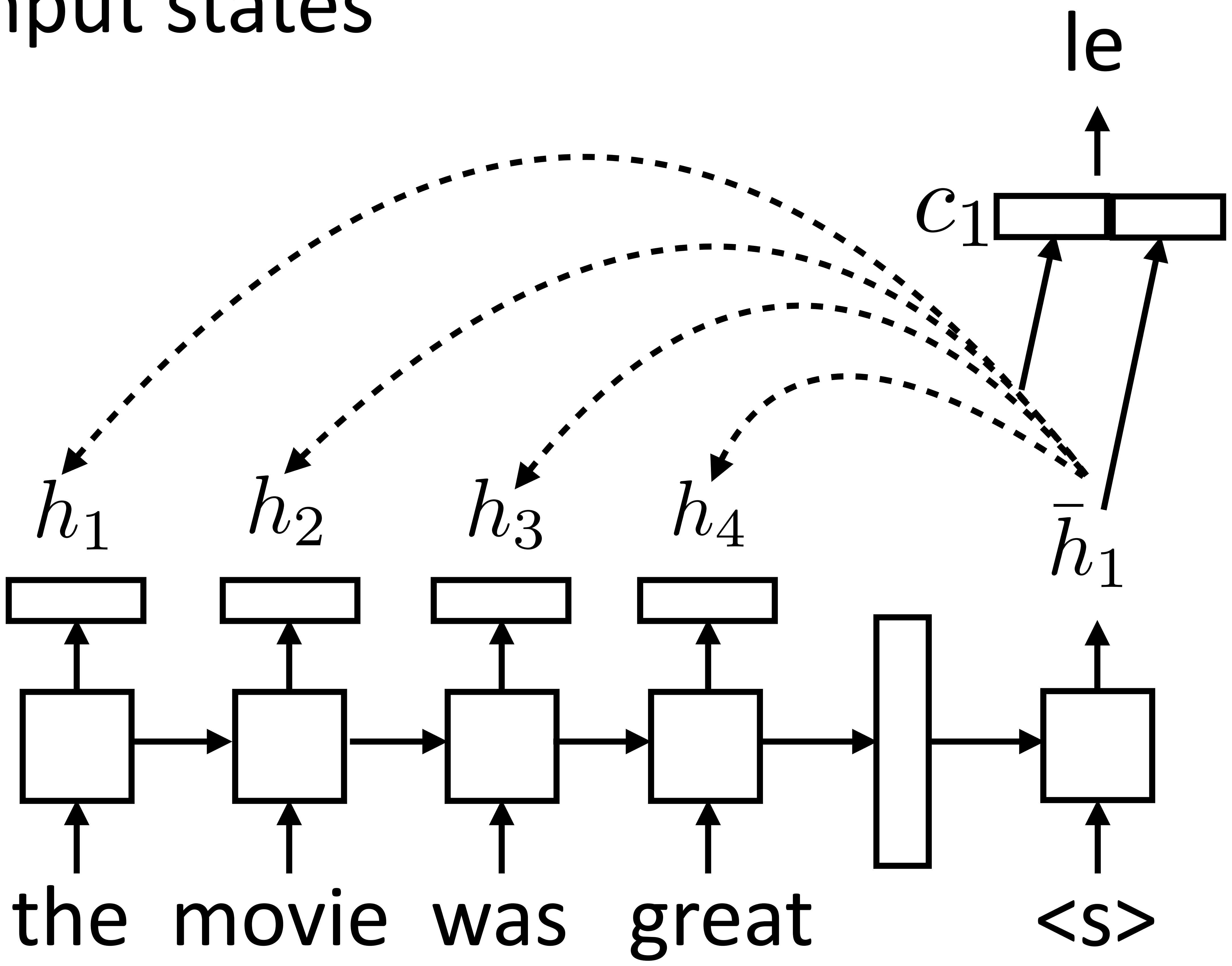

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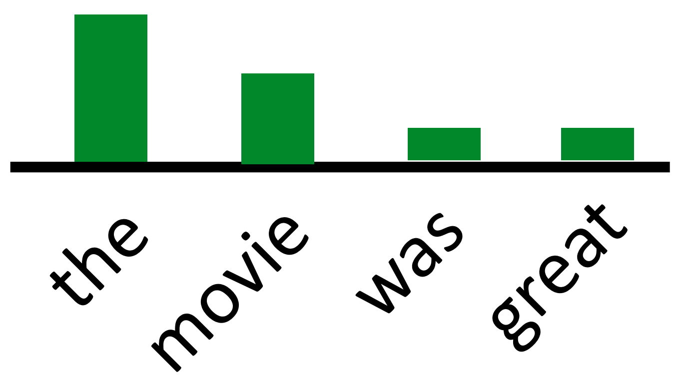

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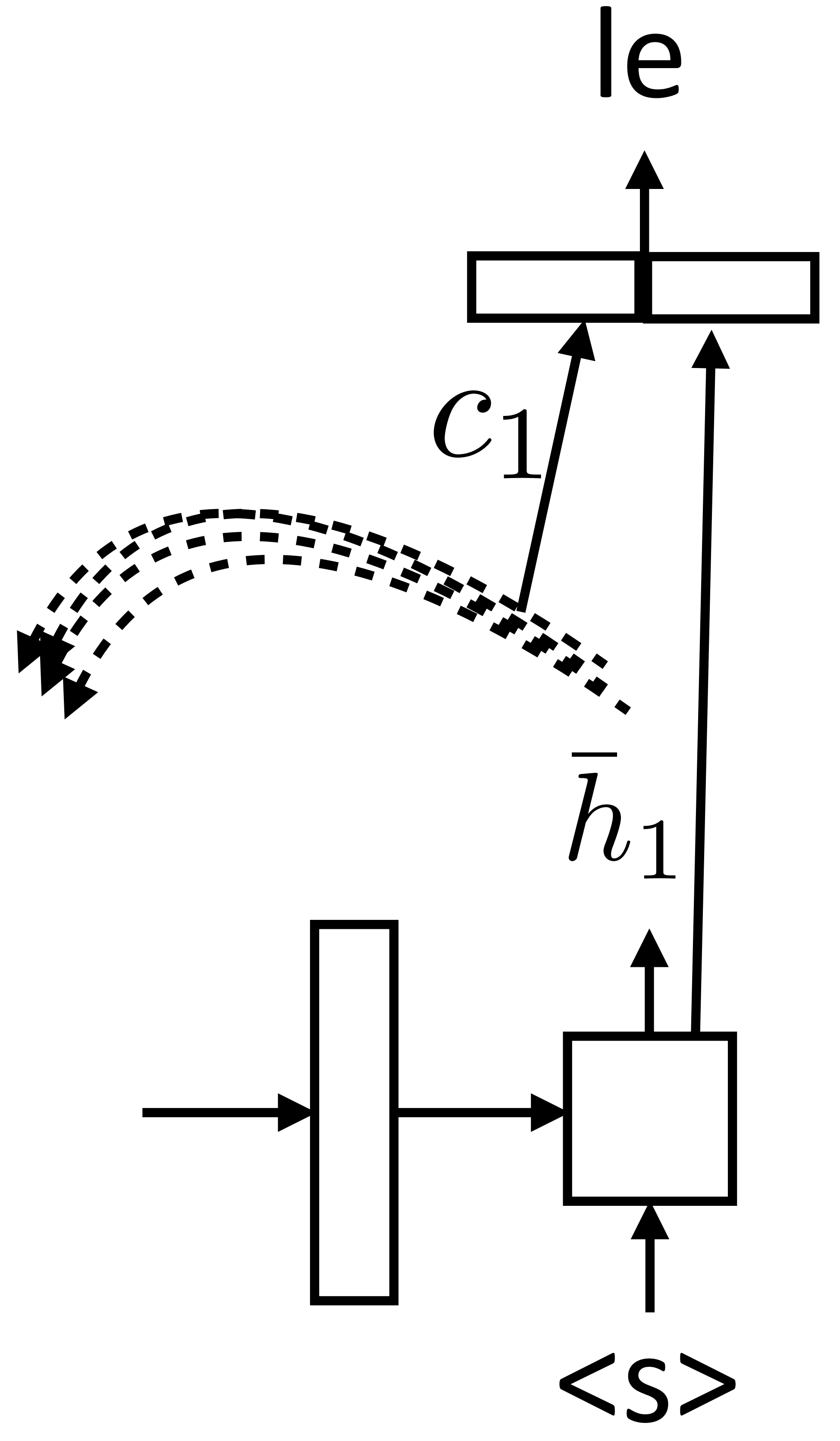

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Luong et al. (2015)

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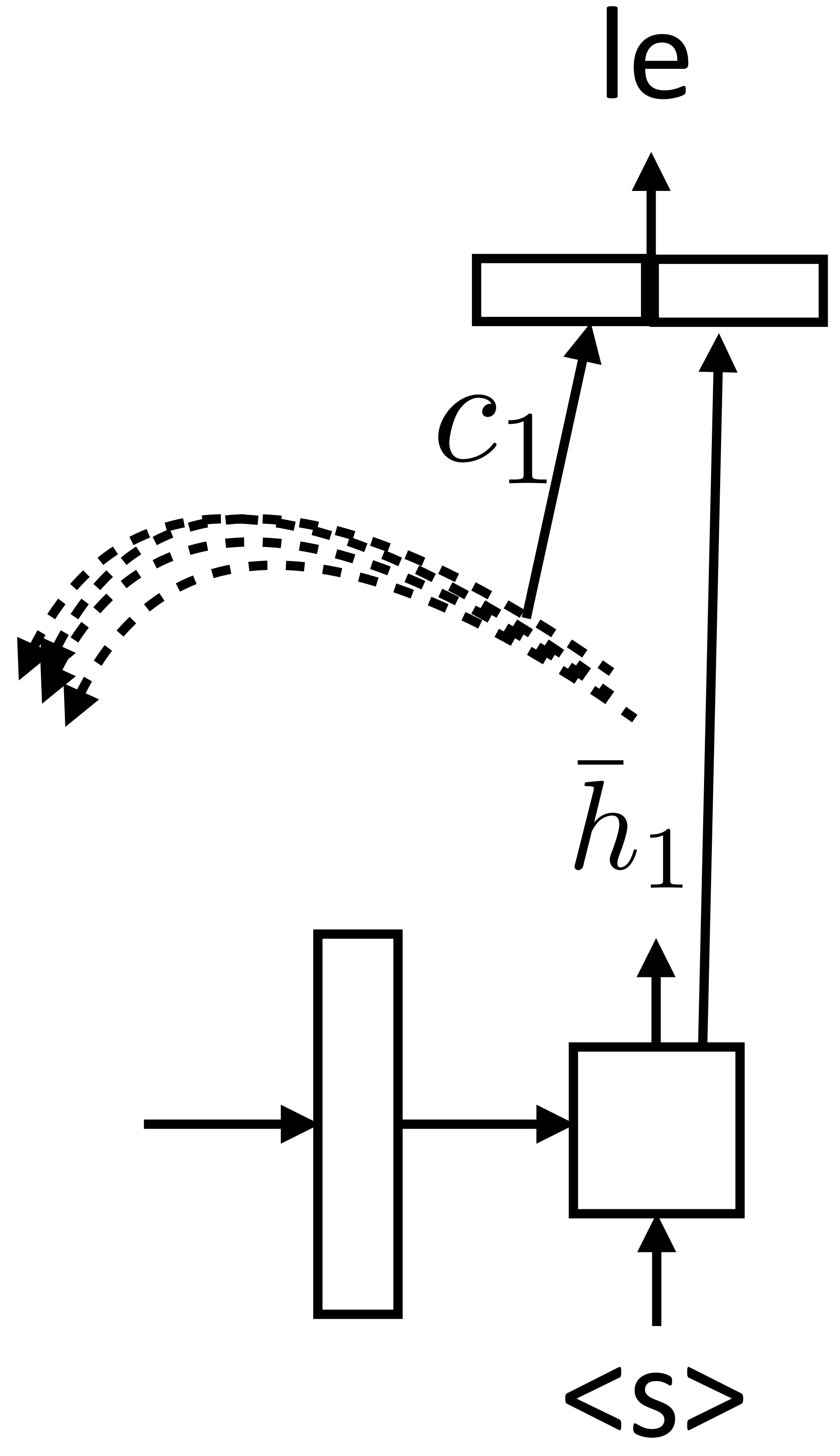

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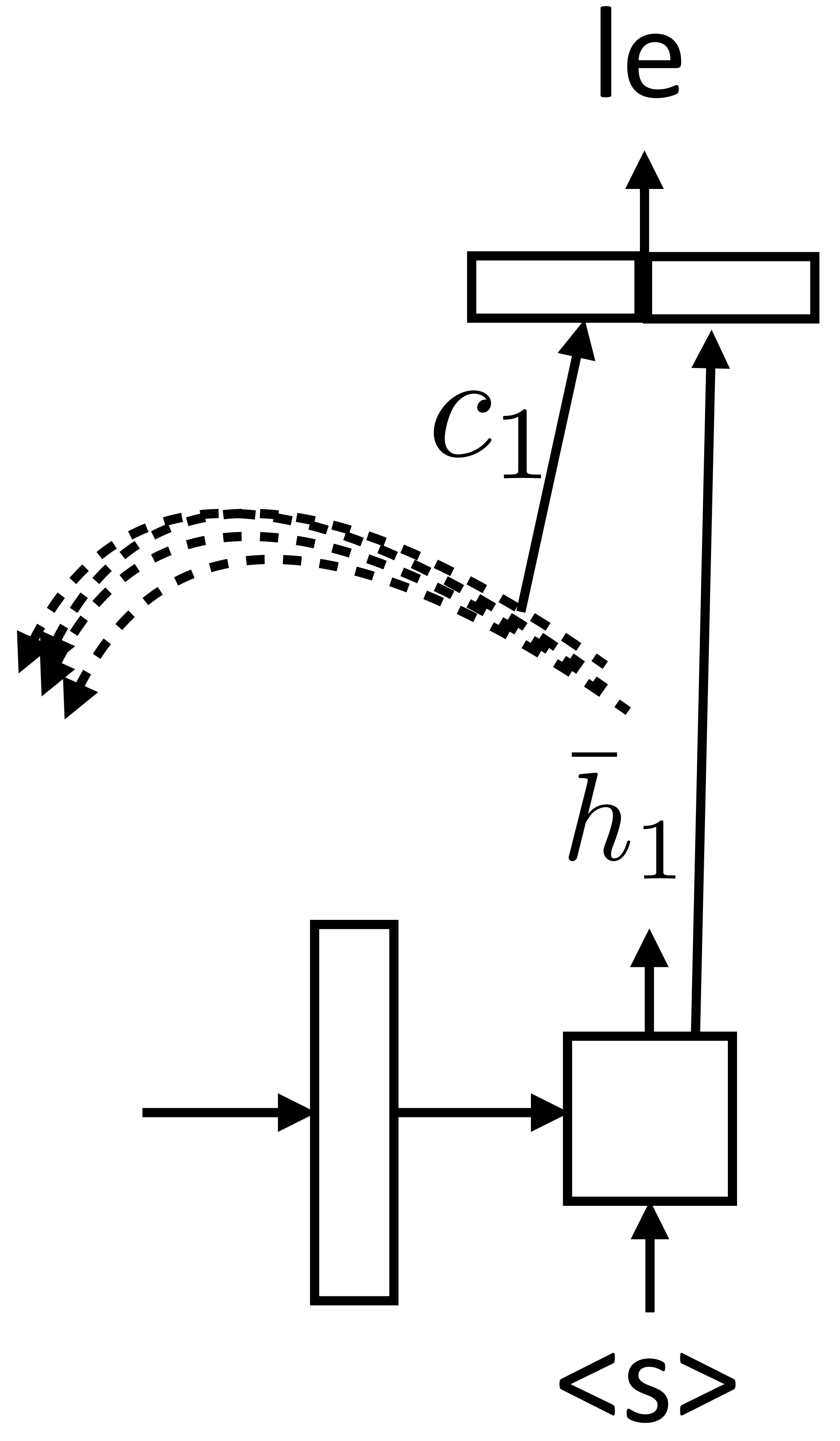

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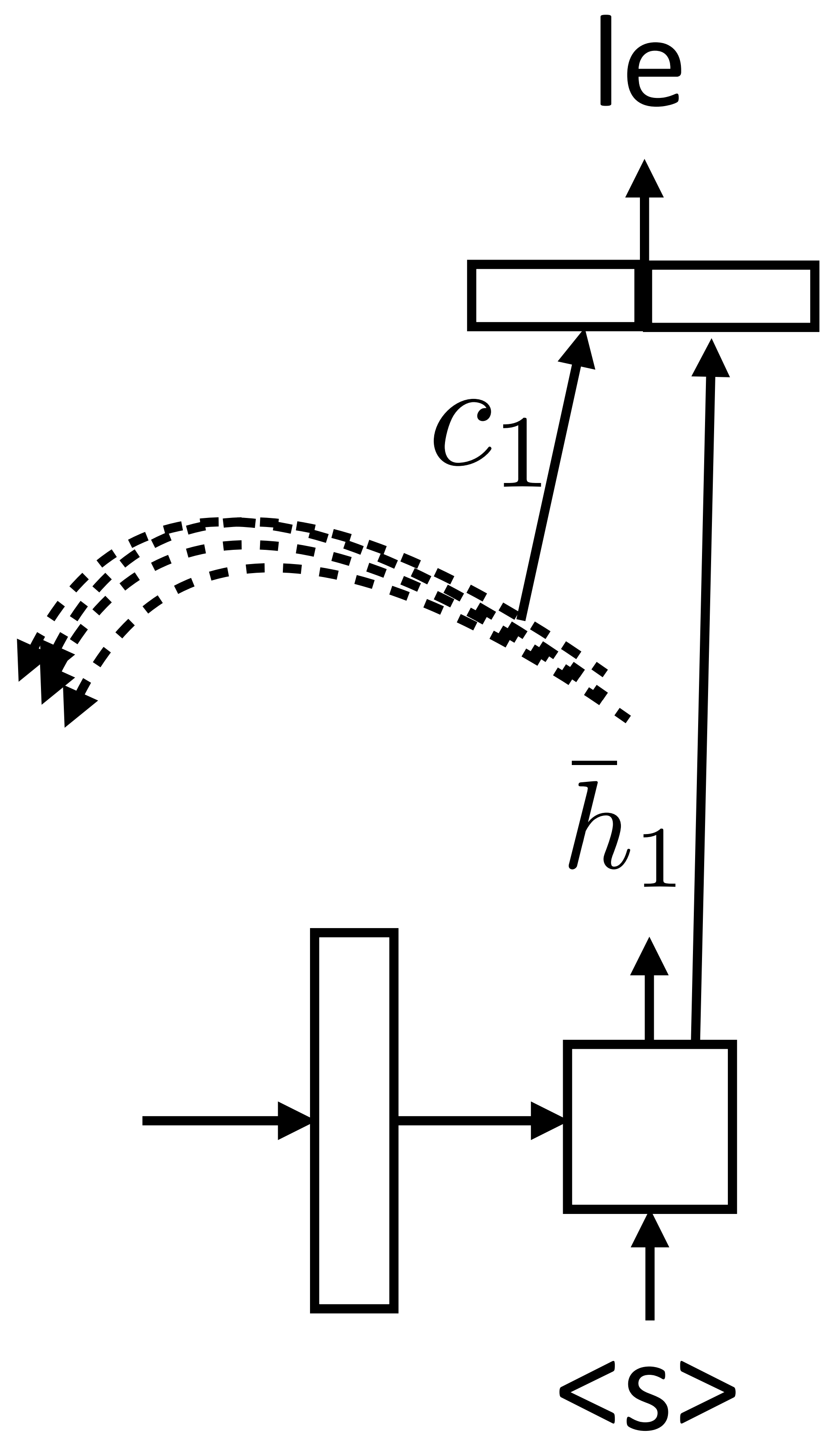

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Luong et al. (2015)

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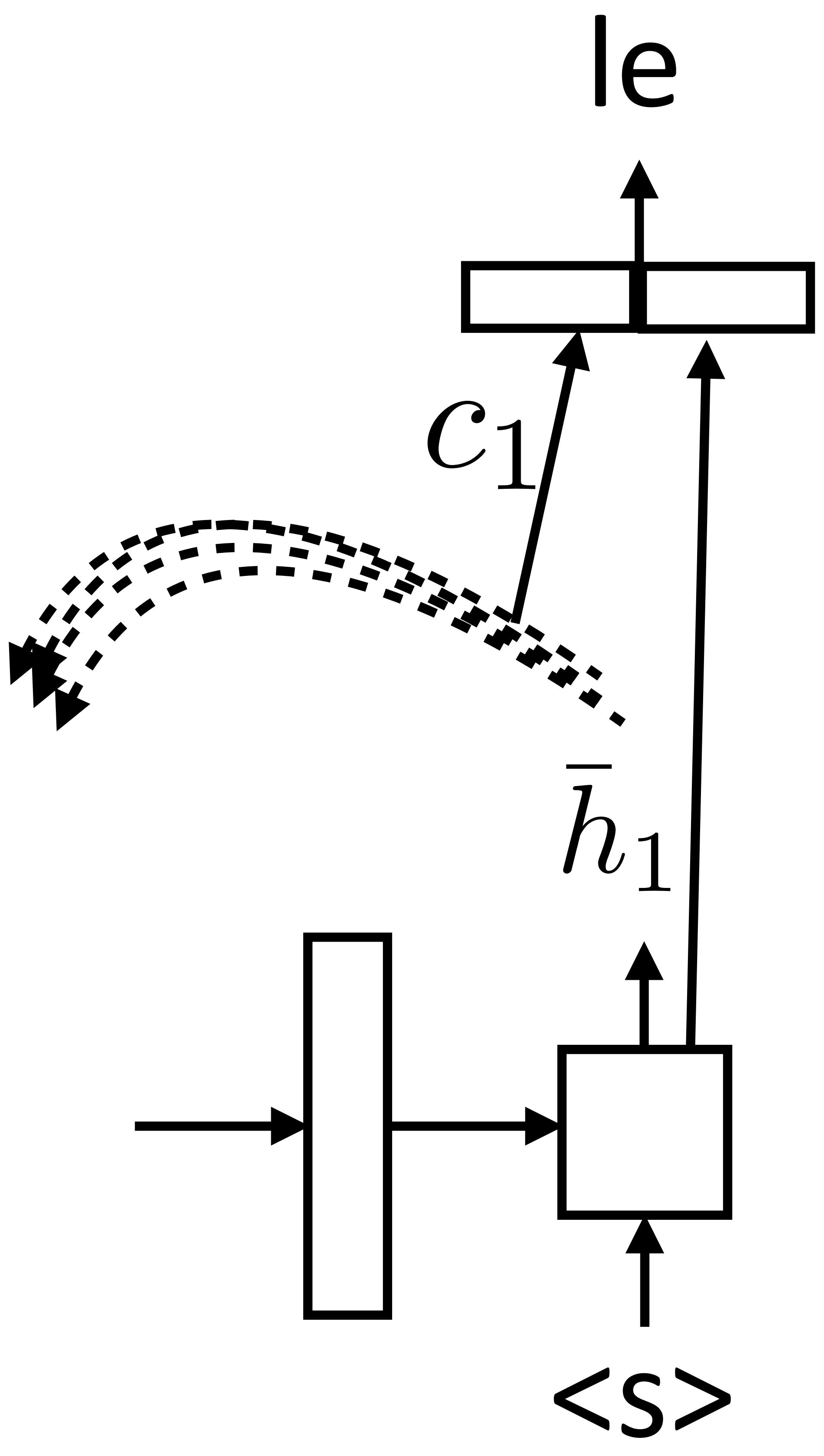

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- Note that this all uses outputs of hidden layers

Luong et al. (2015)

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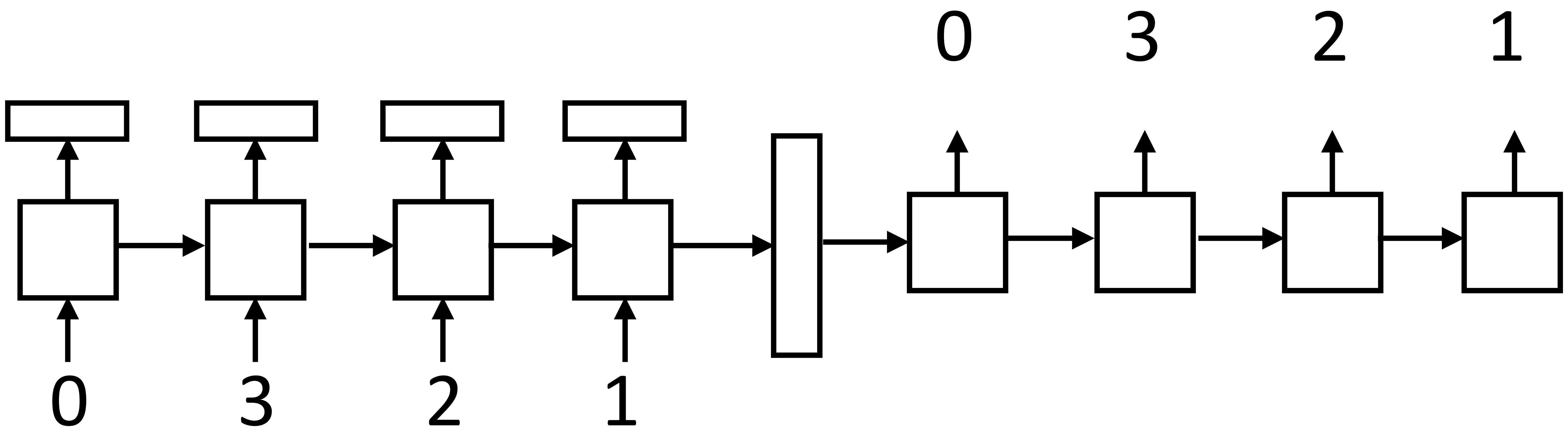
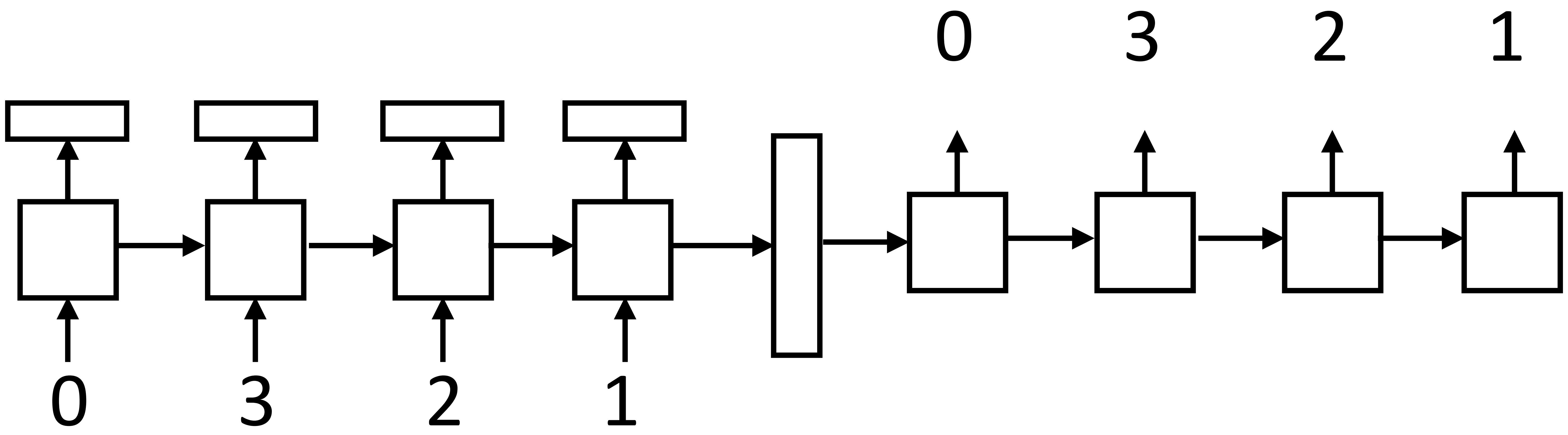


Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?



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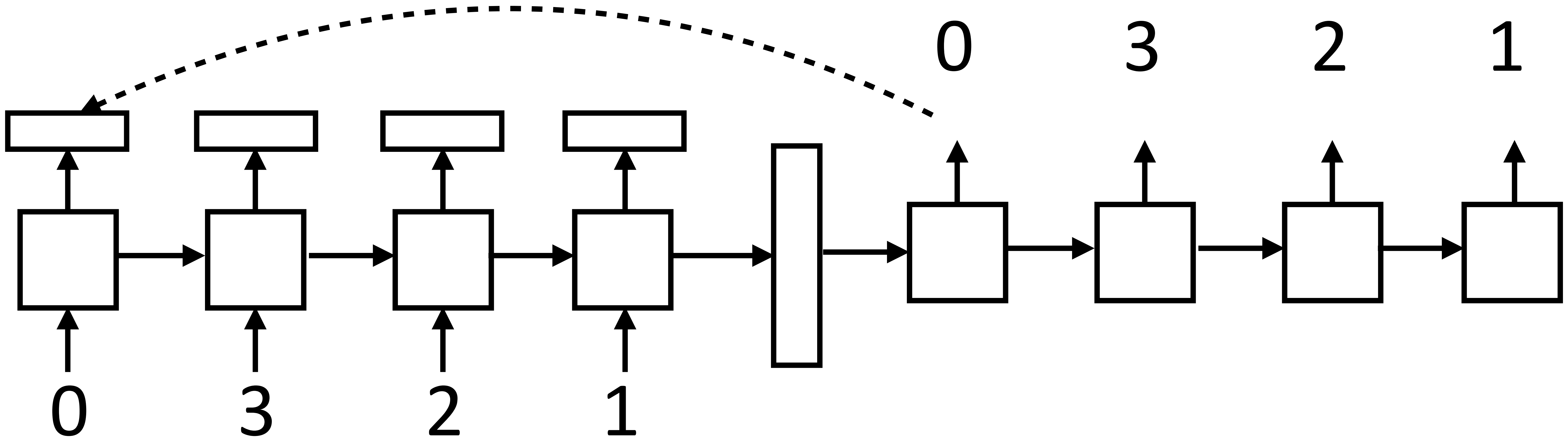
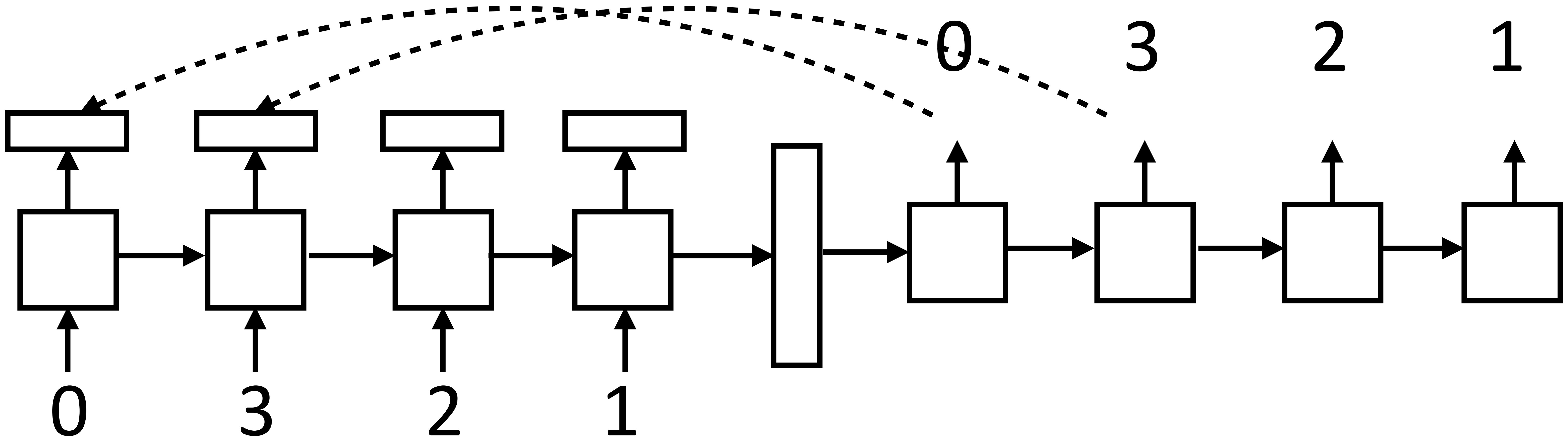


Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?



Luong et al. (2015)

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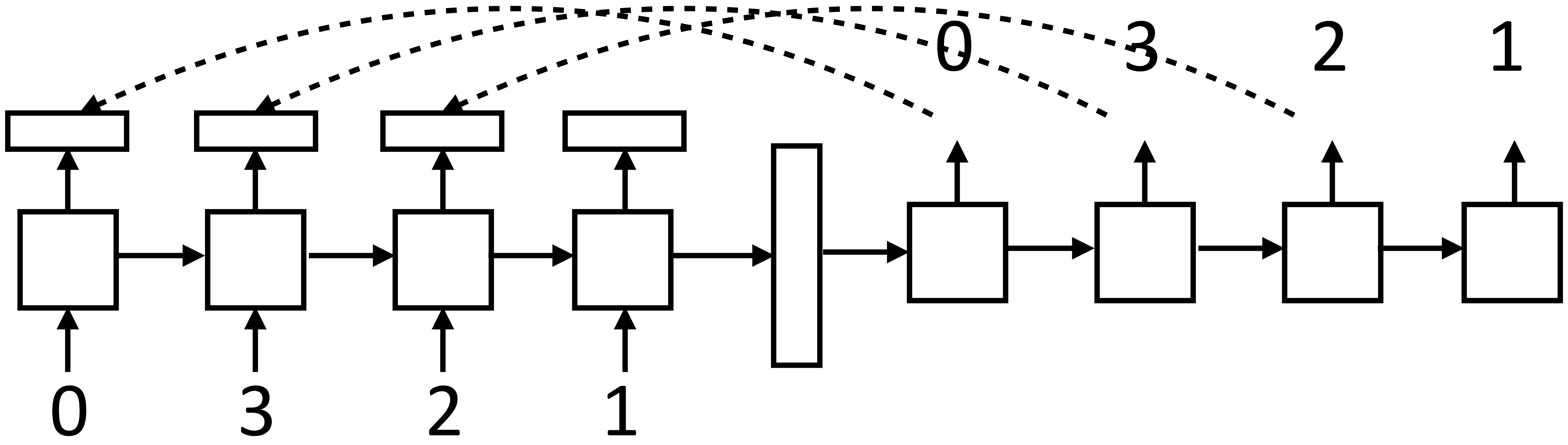
- Learning to copy — how might this work?



Luong et al. (2015)

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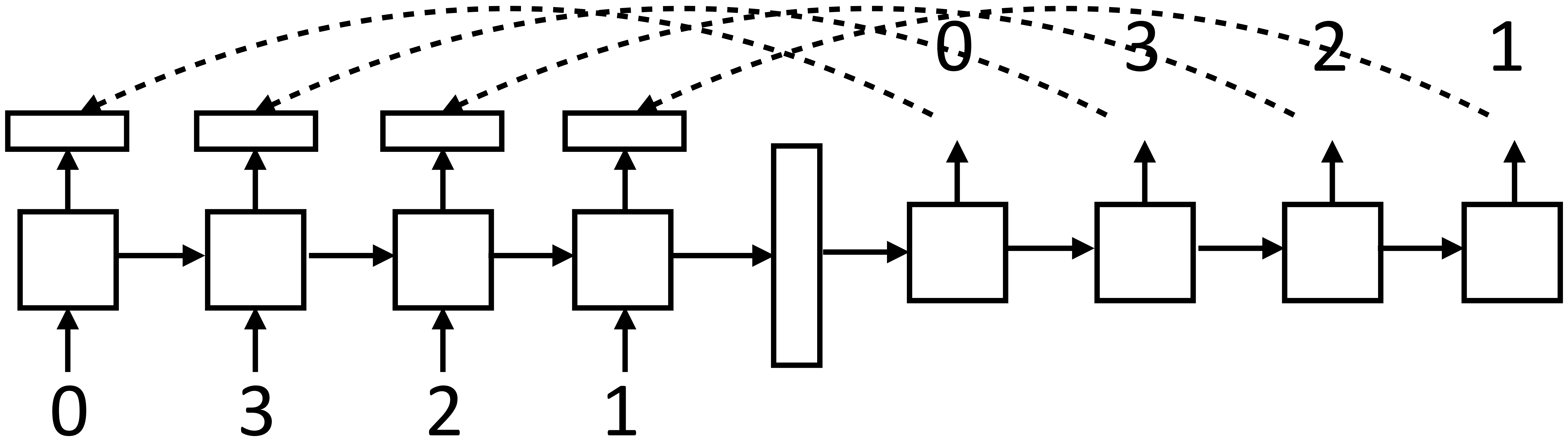

Luong et al. (2015)

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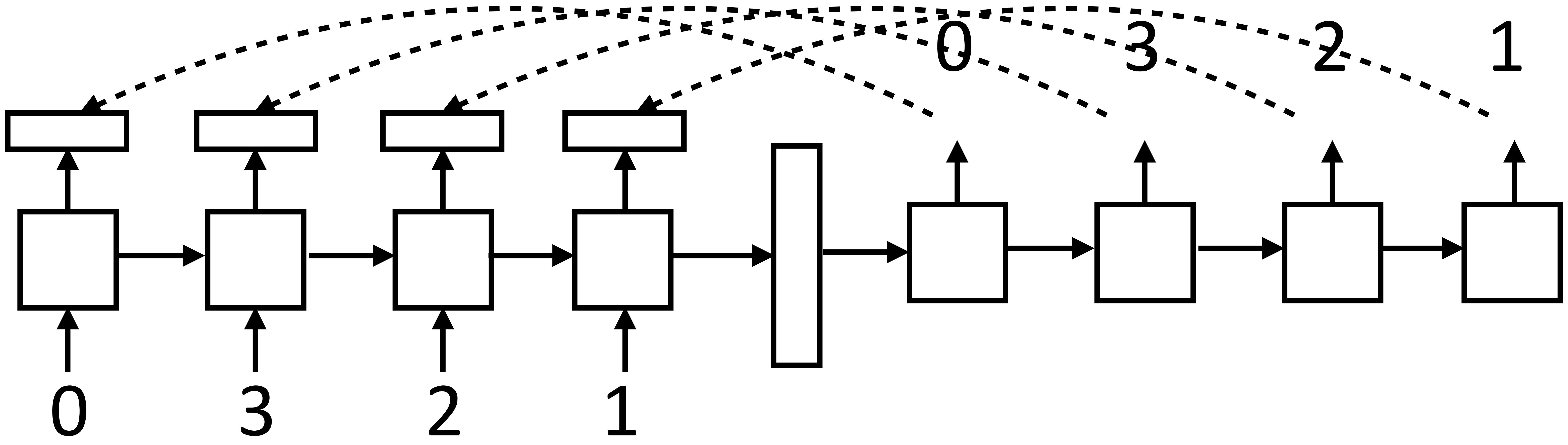
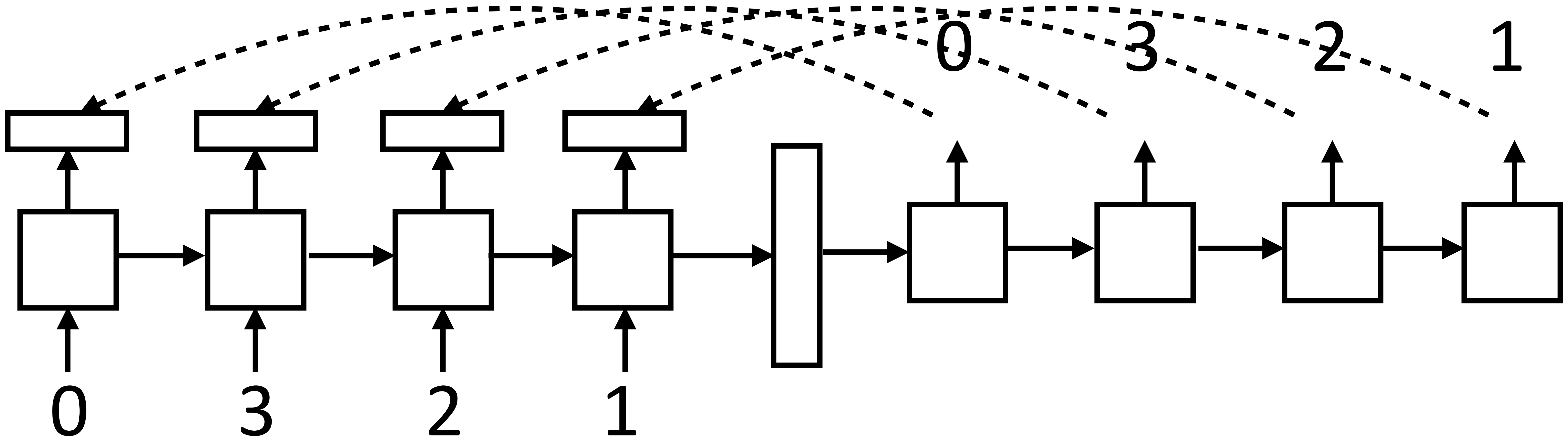


- LSTM can learn to count with the right weight matrix

Luong et al. (2015)

What can attention do?

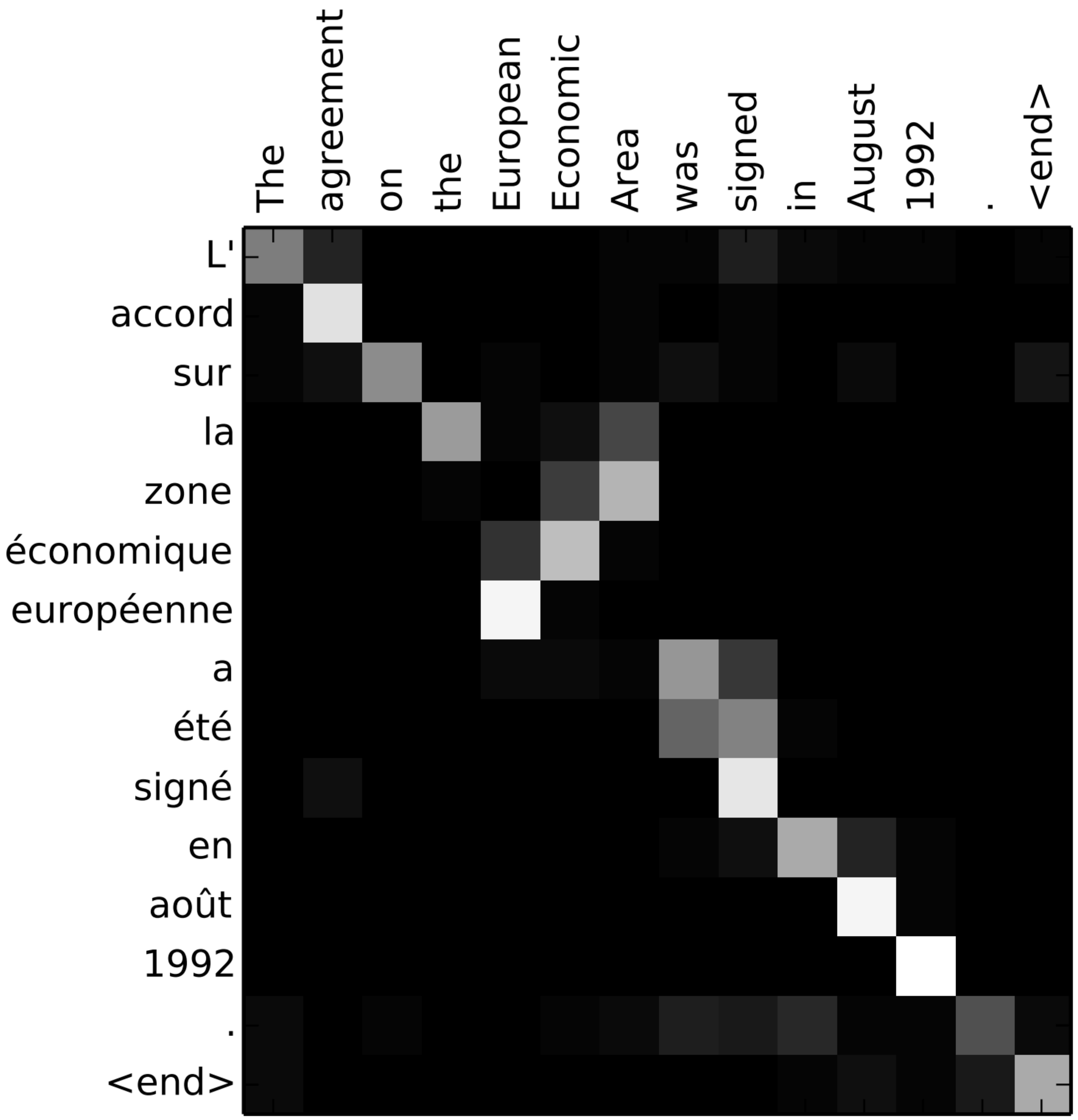
- Learning to copy — how might this work?



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

Luong et al. (2015)

Attention


The
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en
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1992
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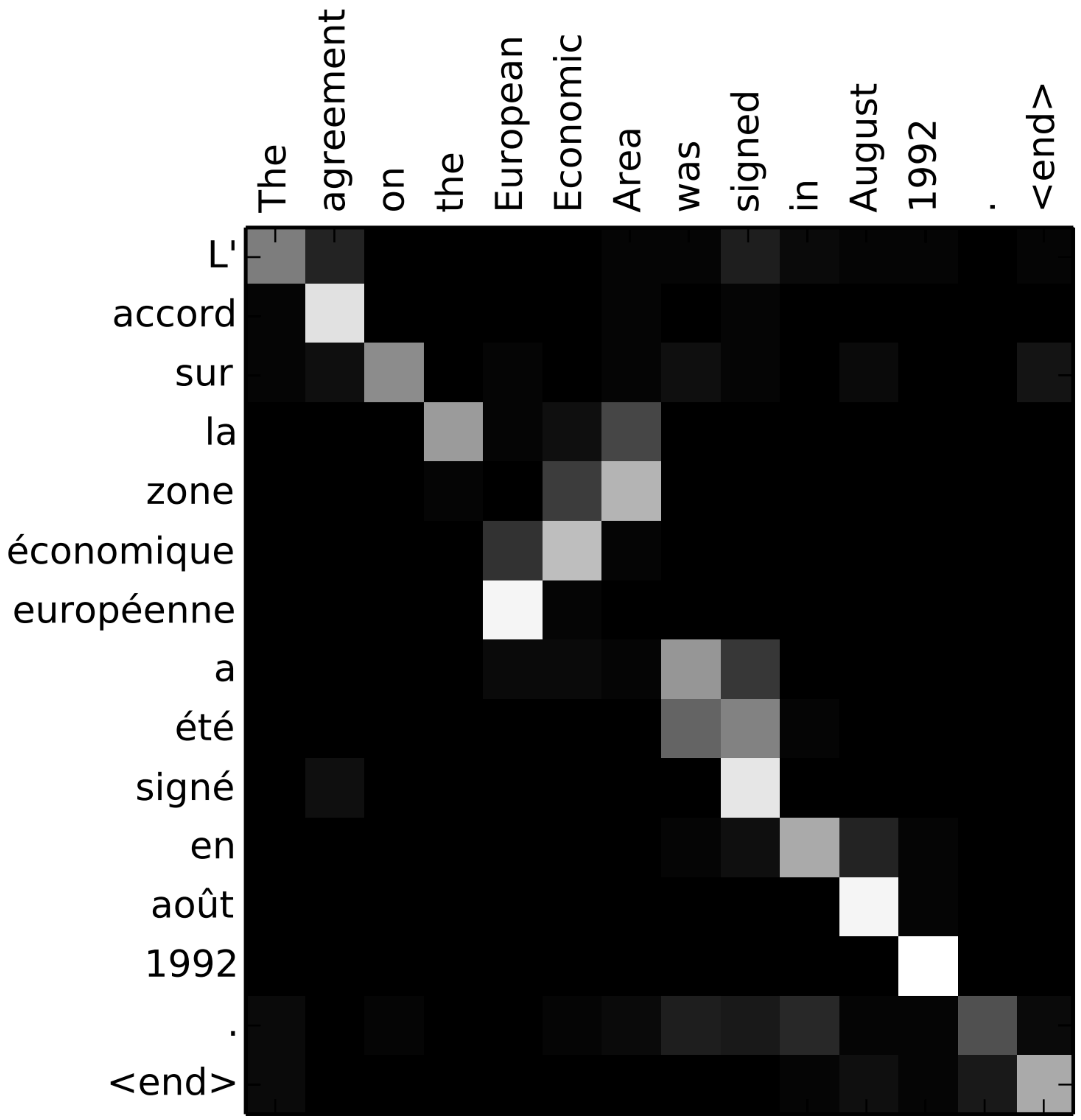
<end>

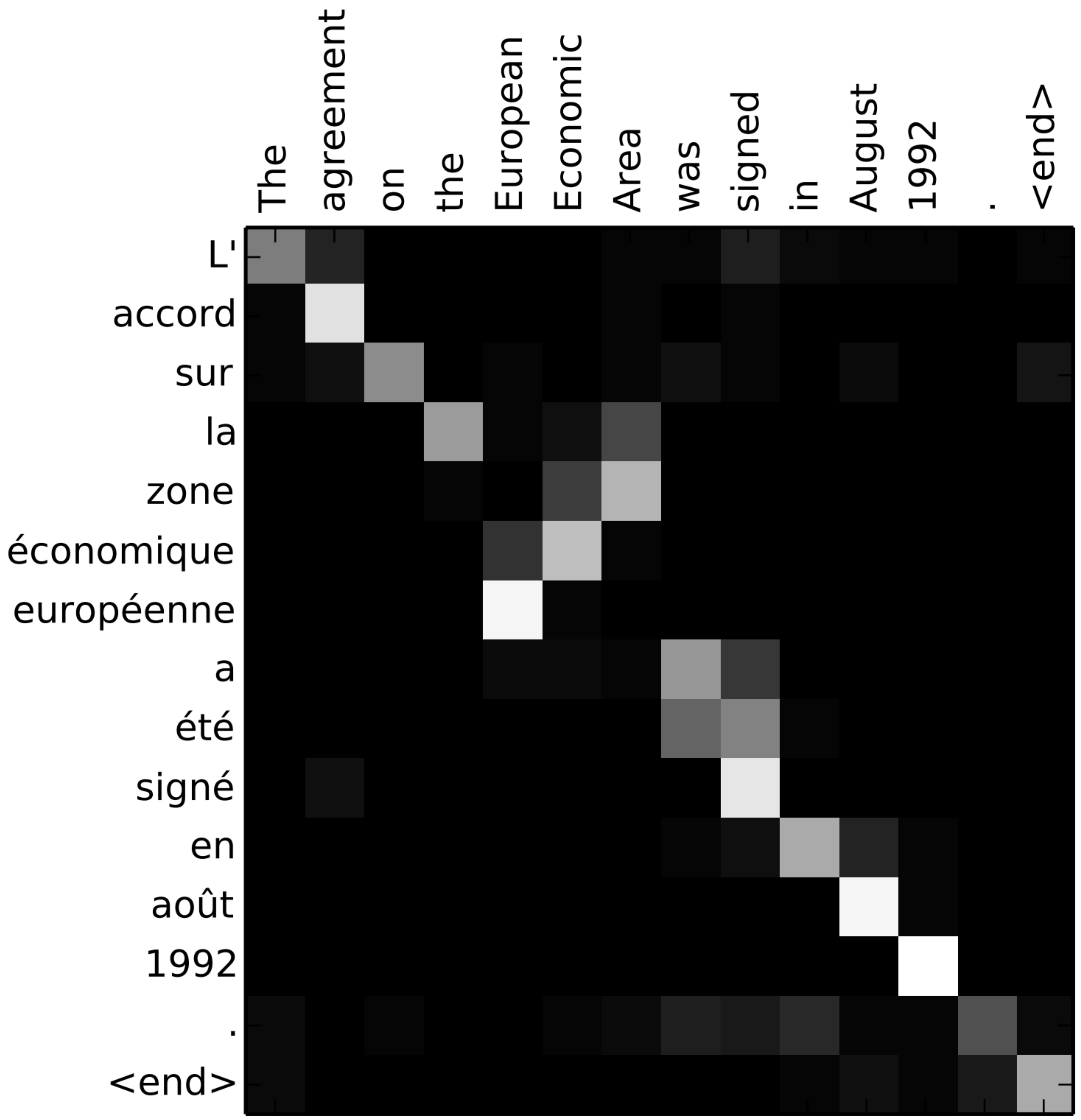
Attention

- Encoder hidden states capture contextual source word identity



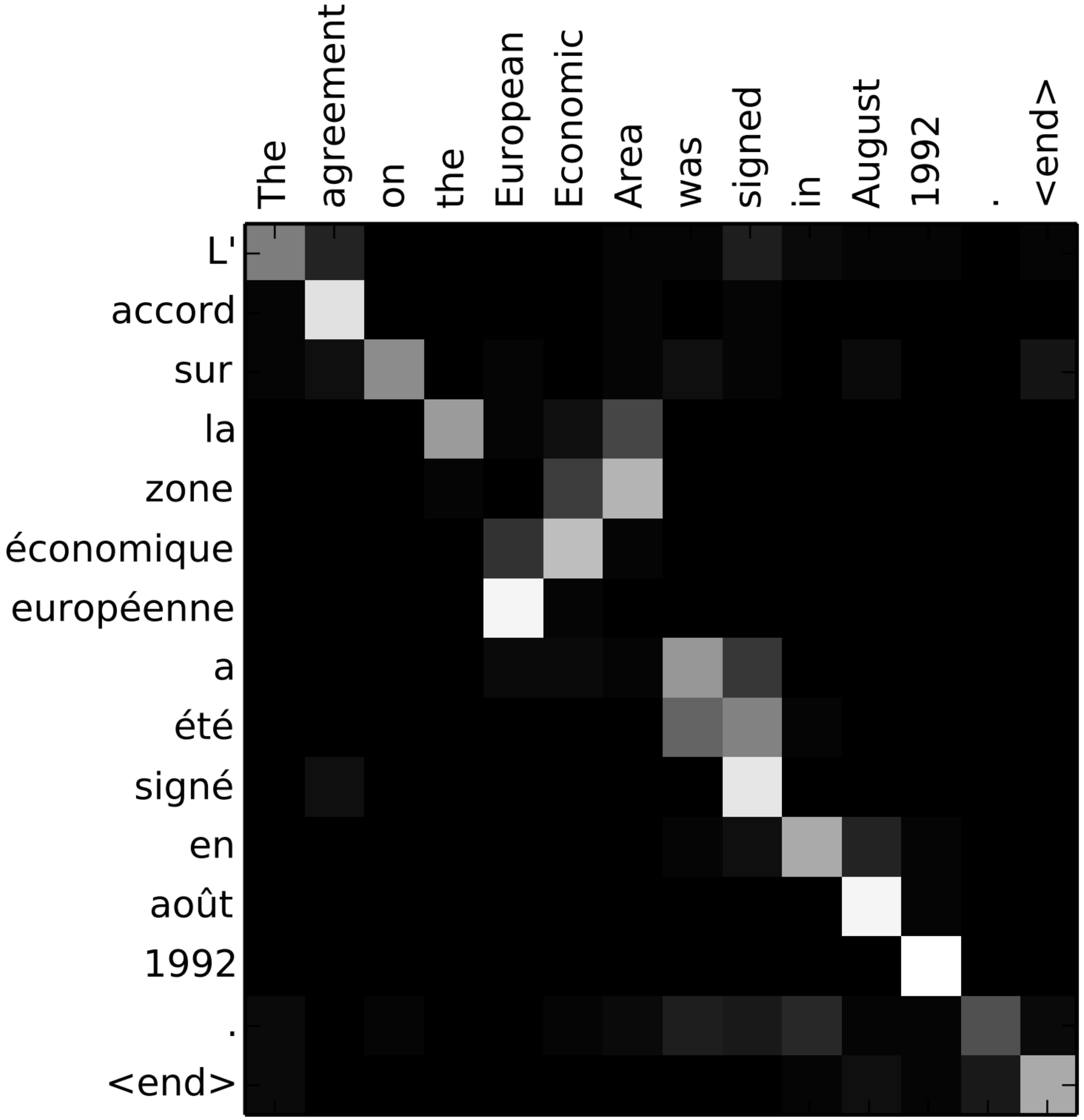
Attention

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

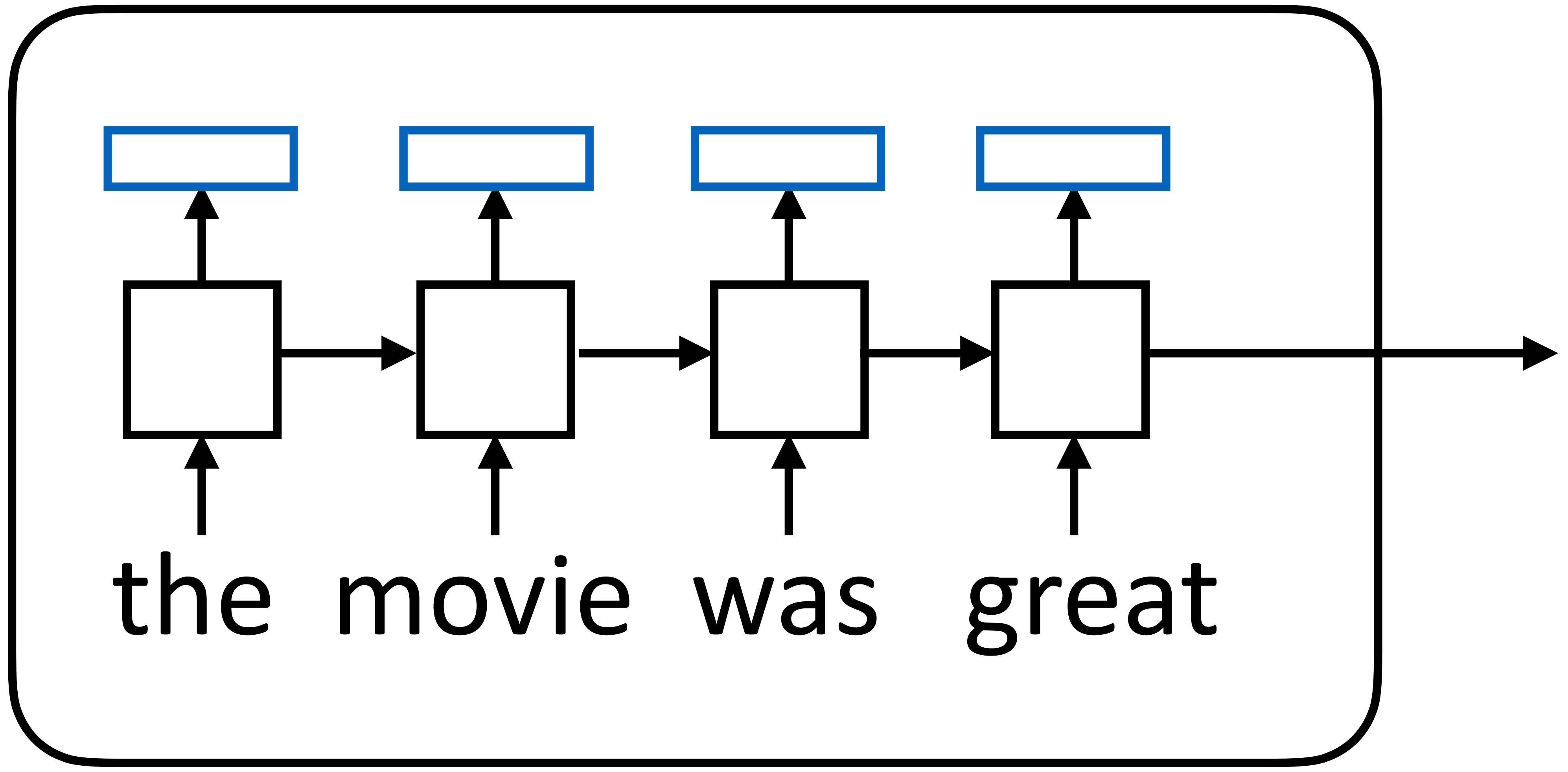


Attention

- 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



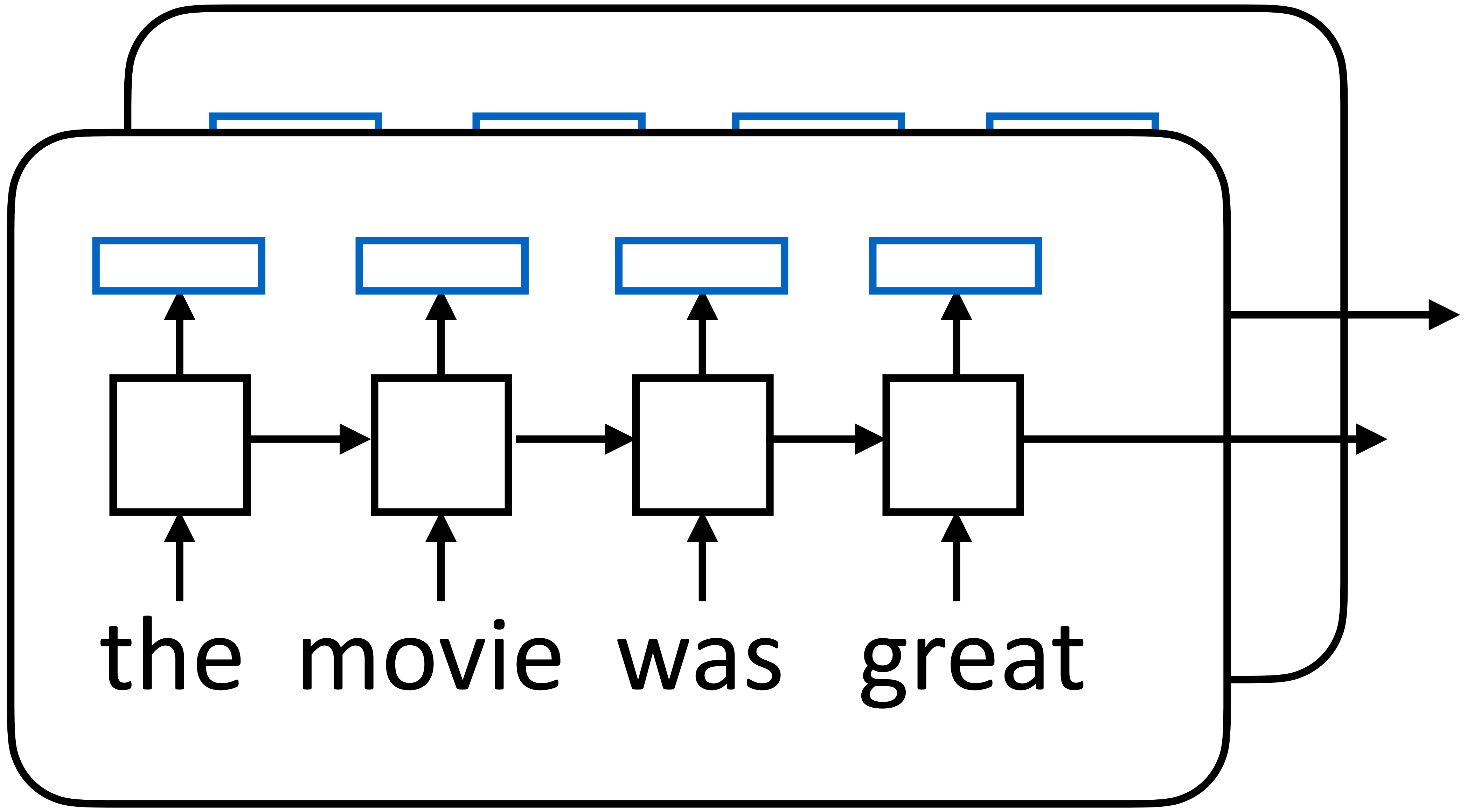
Batching Attention



Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



Luong et al. (2015)

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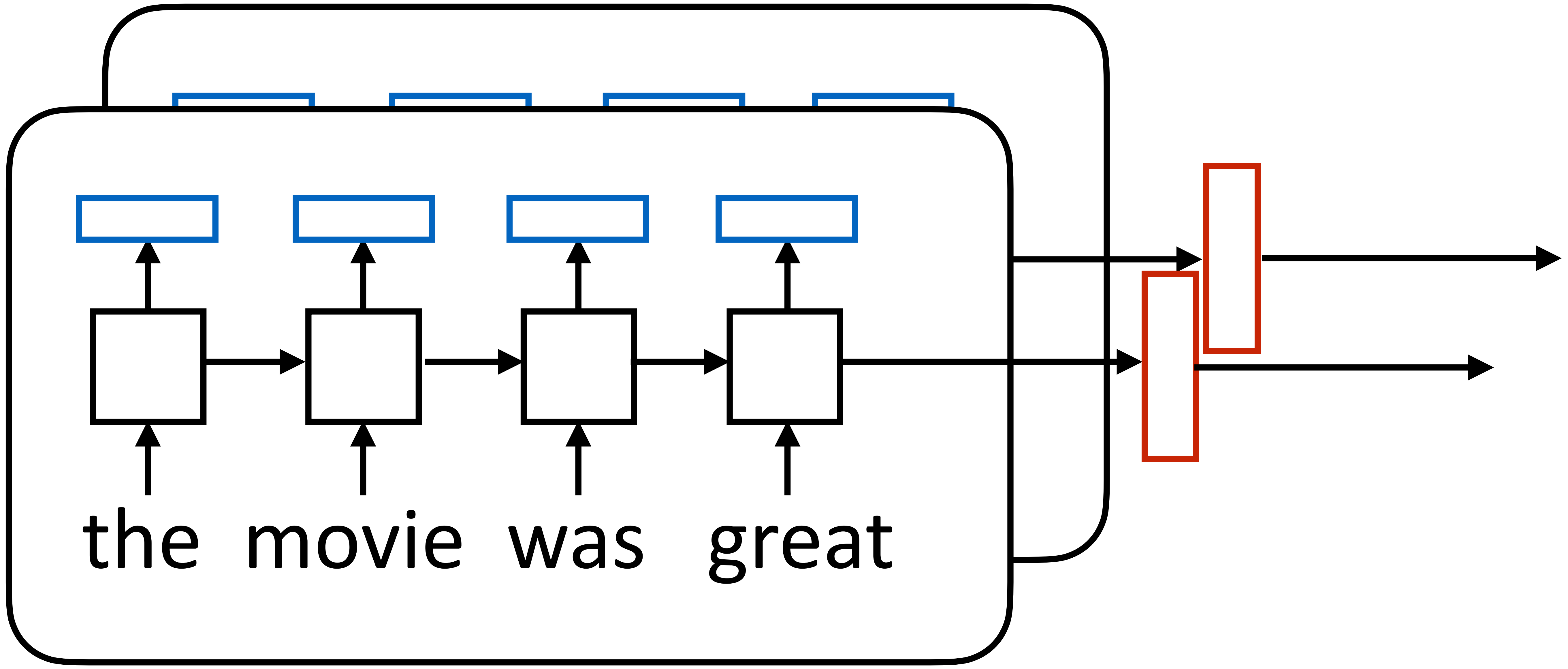

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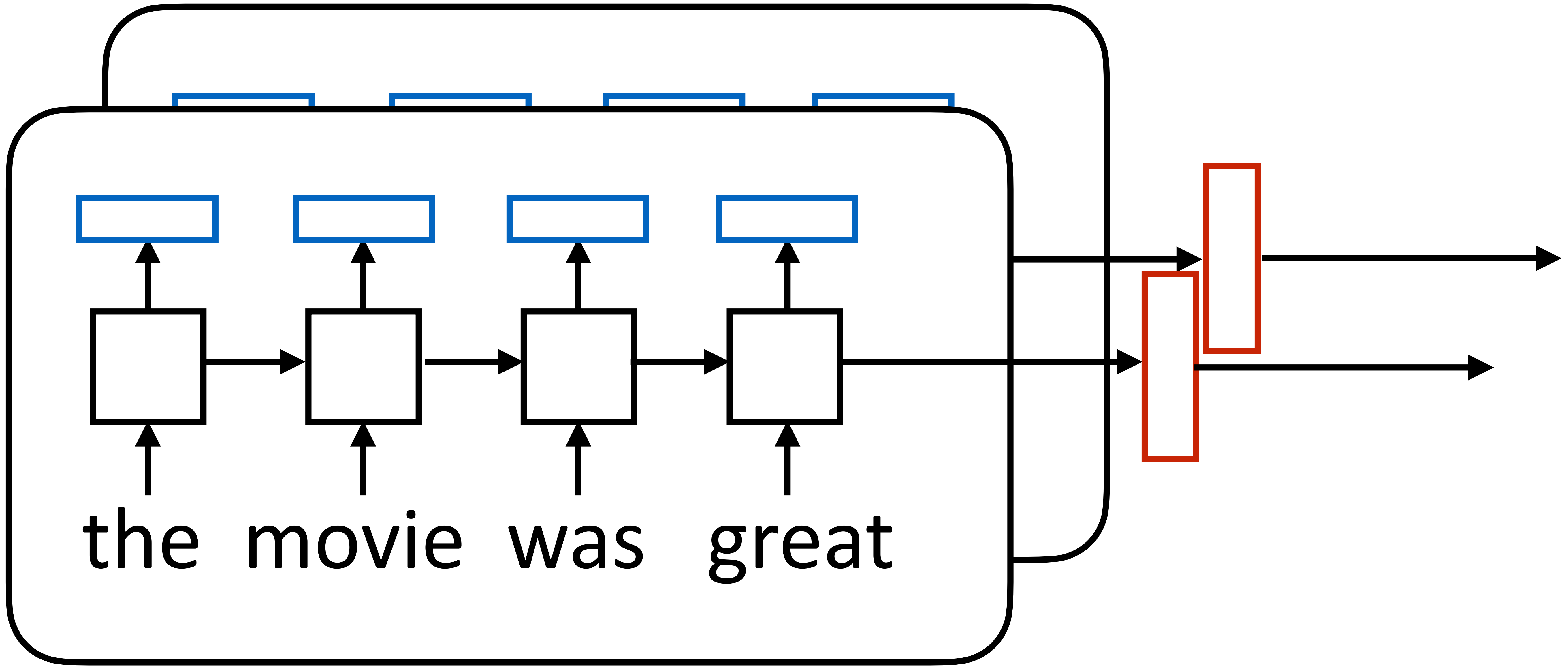

sentence outputs:
batch size x hidden size

Luong et al. (2015)

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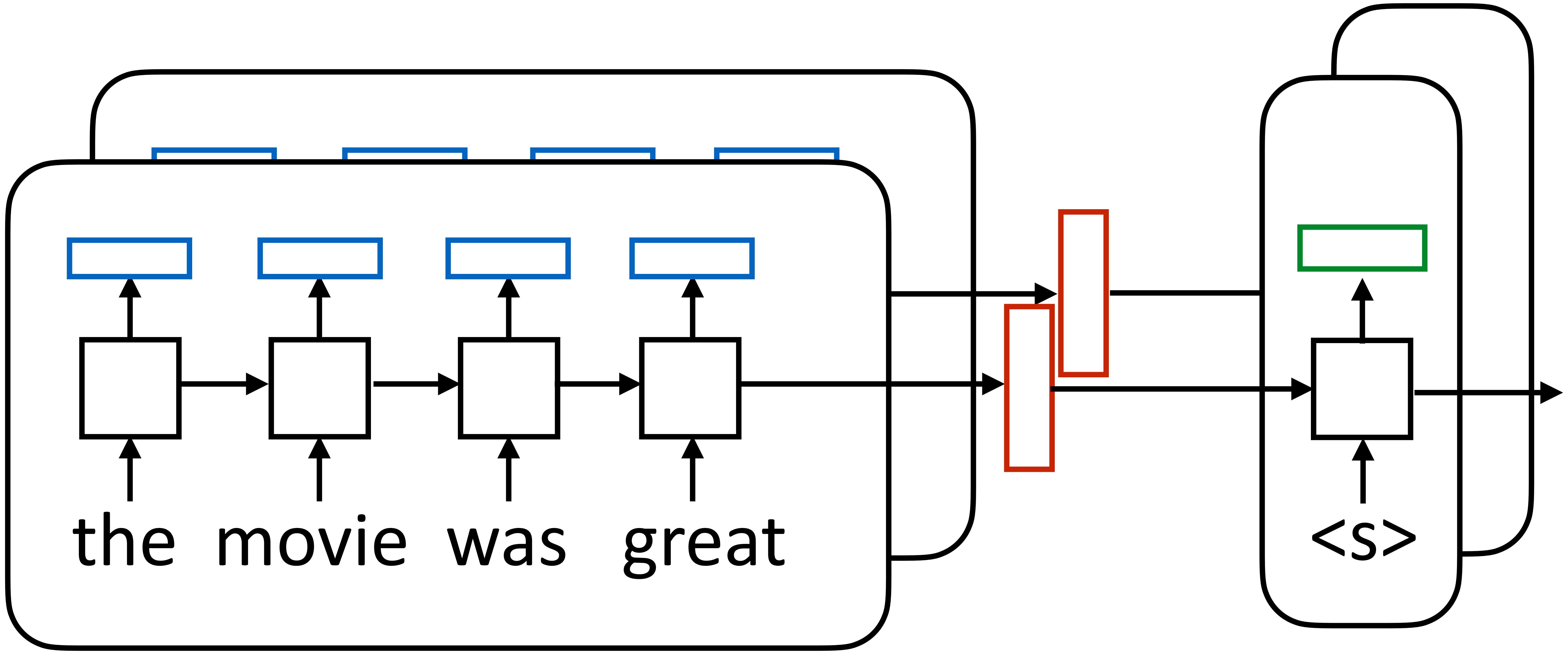

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Luong et al. (2015)

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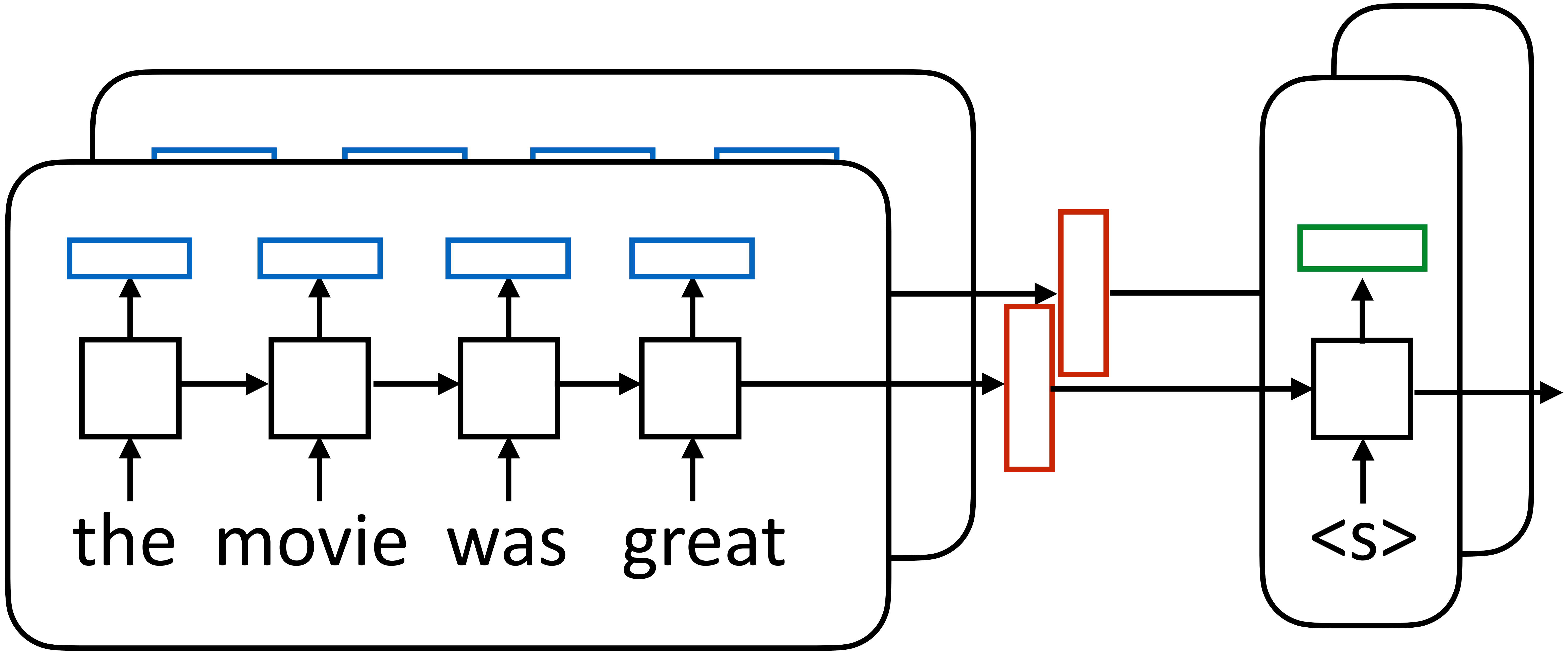


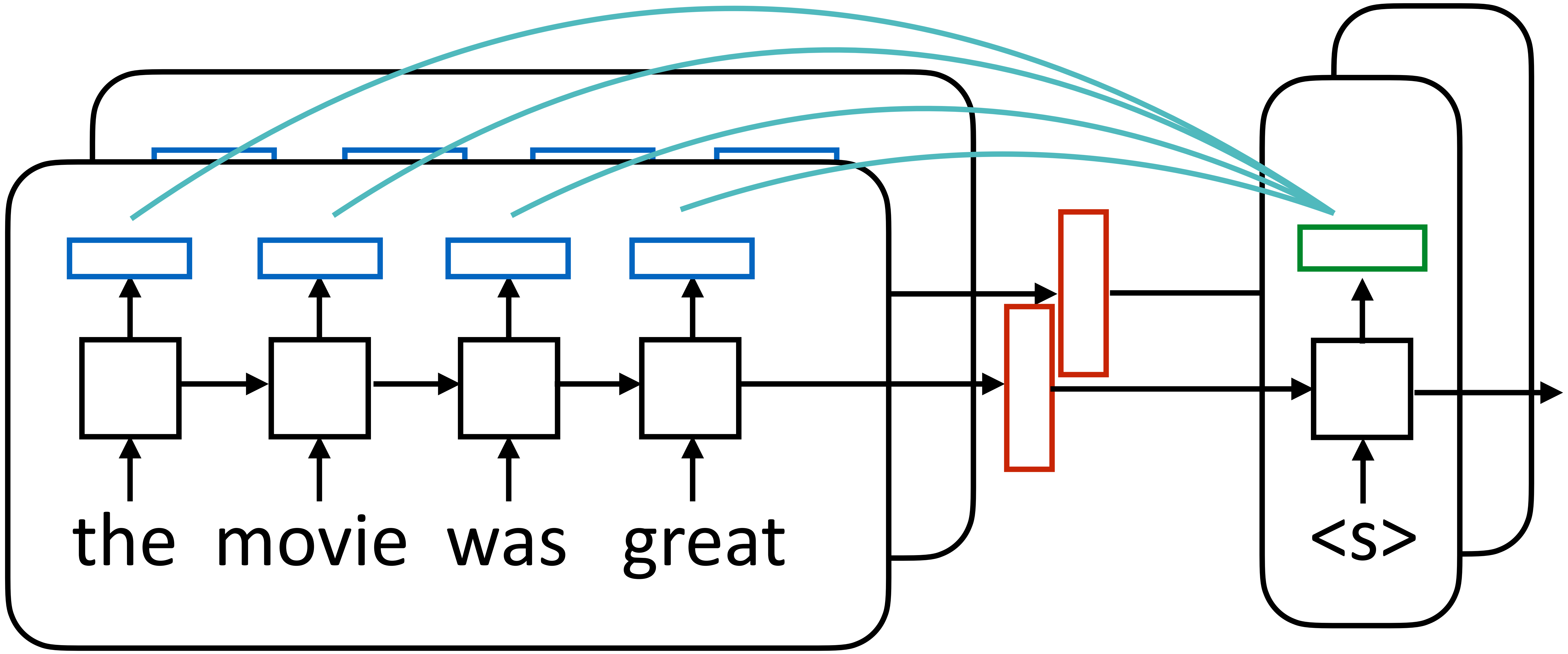
hidden state: batch size x hidden size

sentence outputs: batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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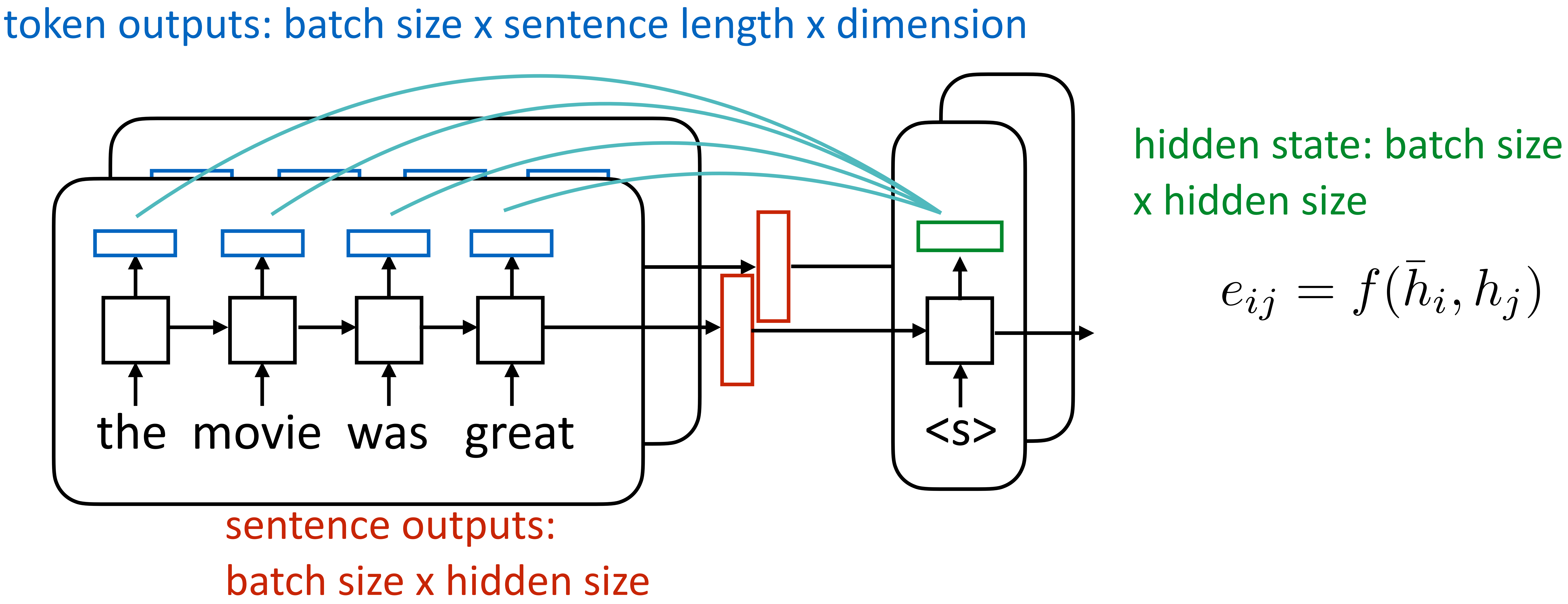
Batching Attention



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

Luong et al. (2015)

Batching Attention

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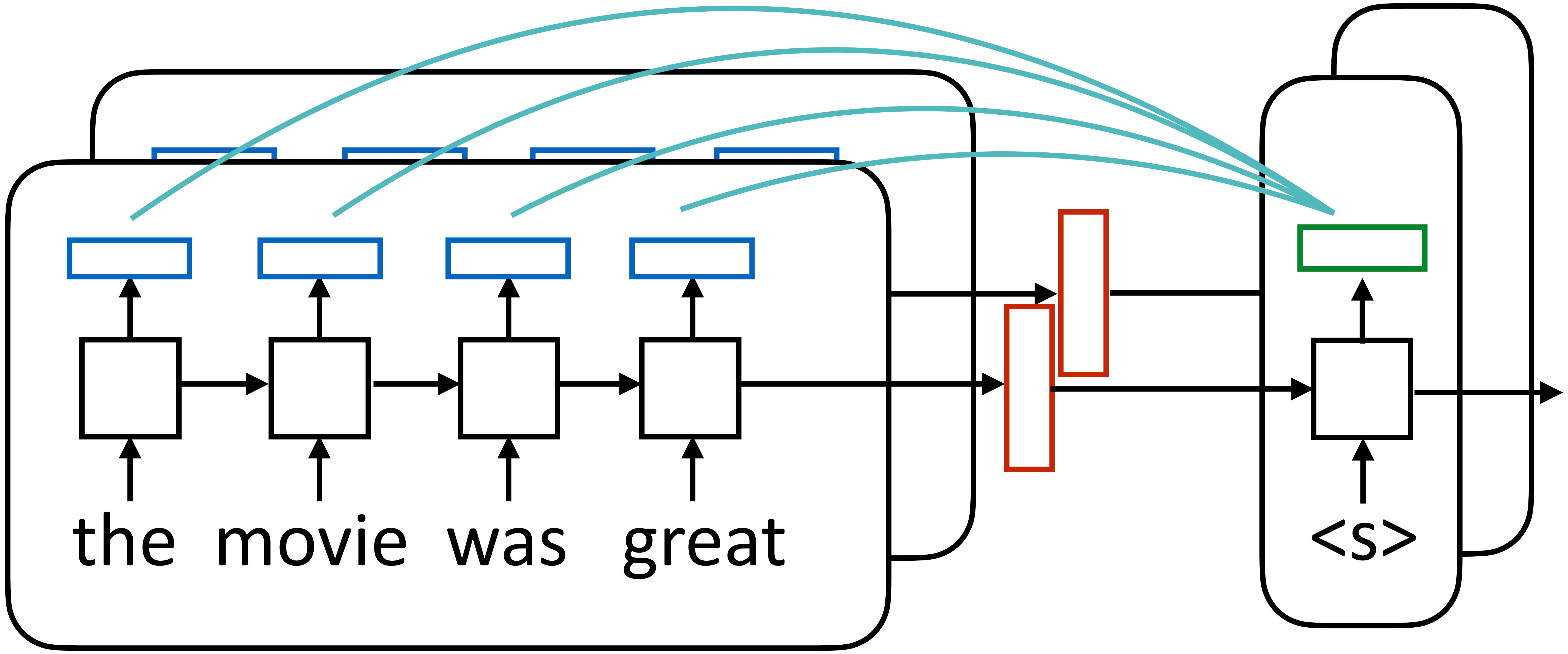


hidden state: batch size x hidden size

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

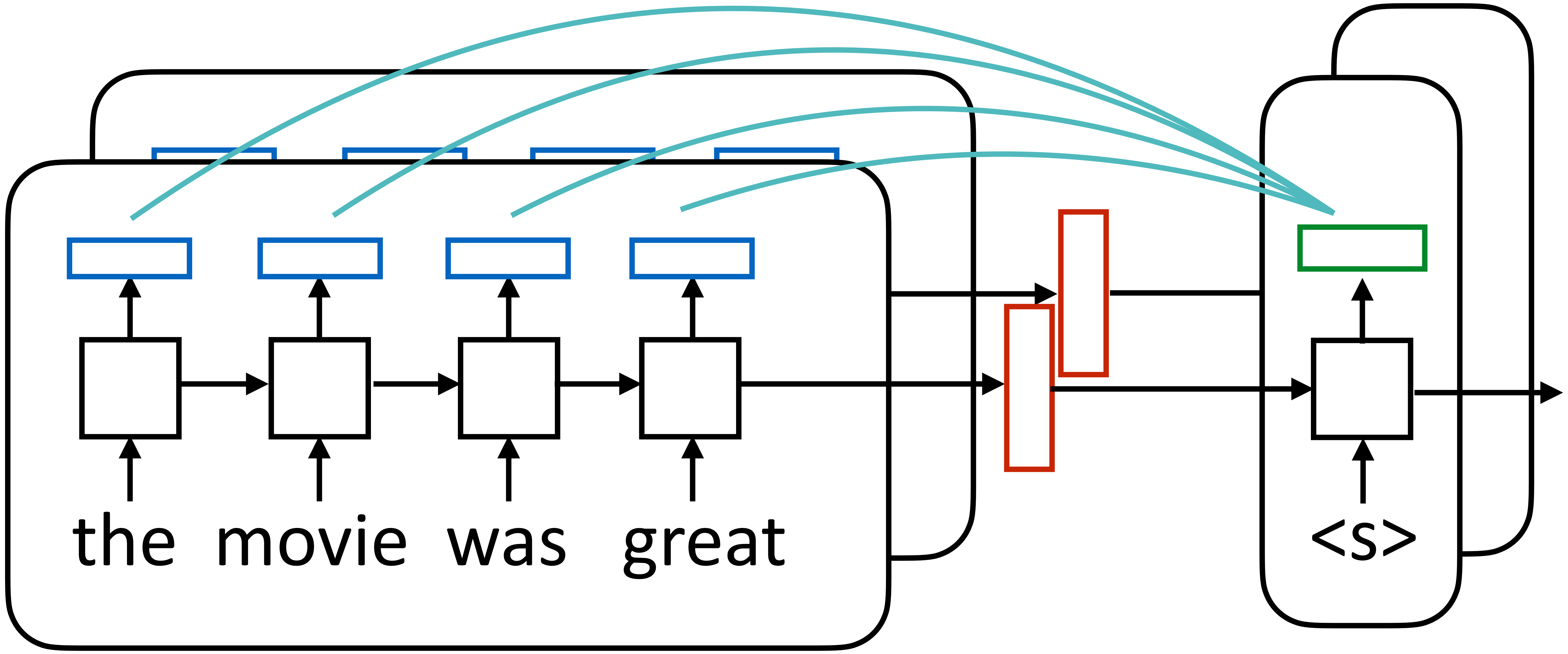
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

sentence outputs:
batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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sentence outputs: batch size x hidden size

attention scores = batch size x sentence length

Luong et al. (2015)

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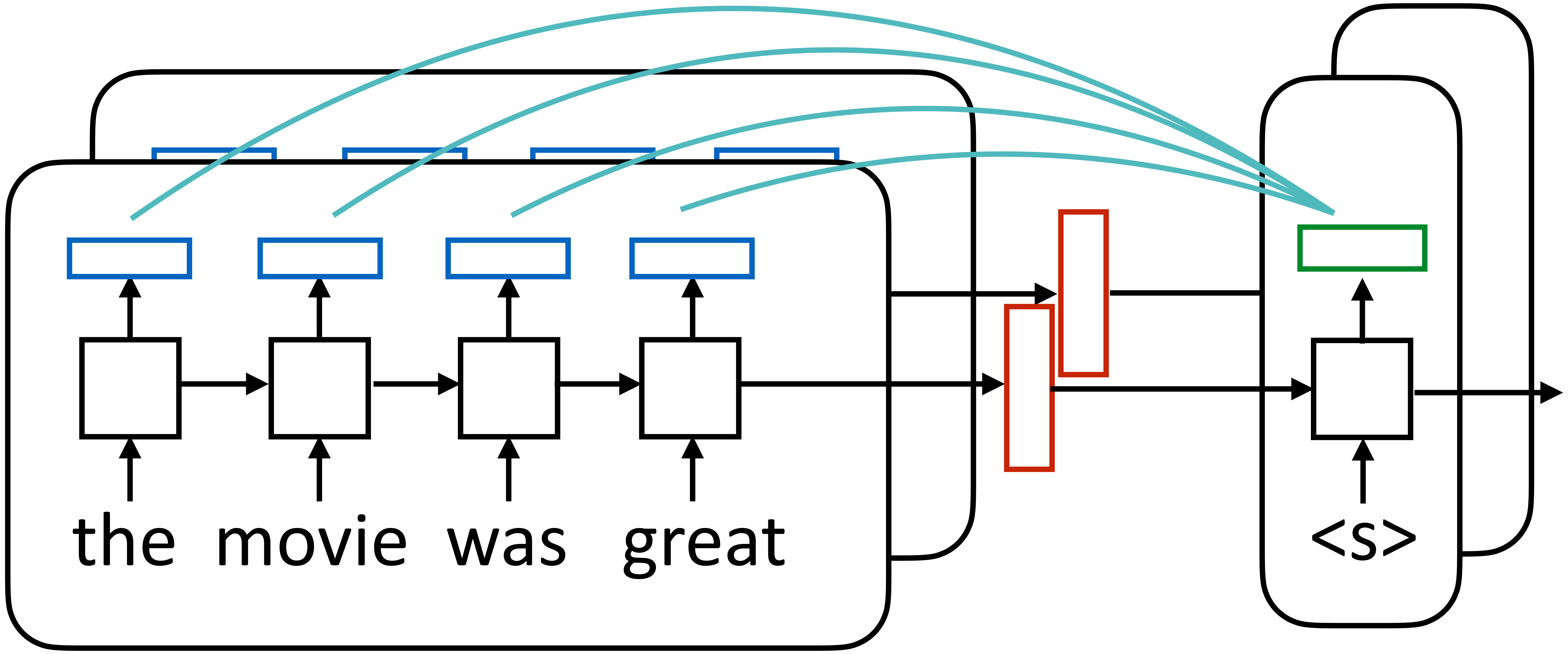
token outputs: batch size x sentence length x dimension



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sentence outputs: batch size x hidden size

attention scores = batch size x sentence length

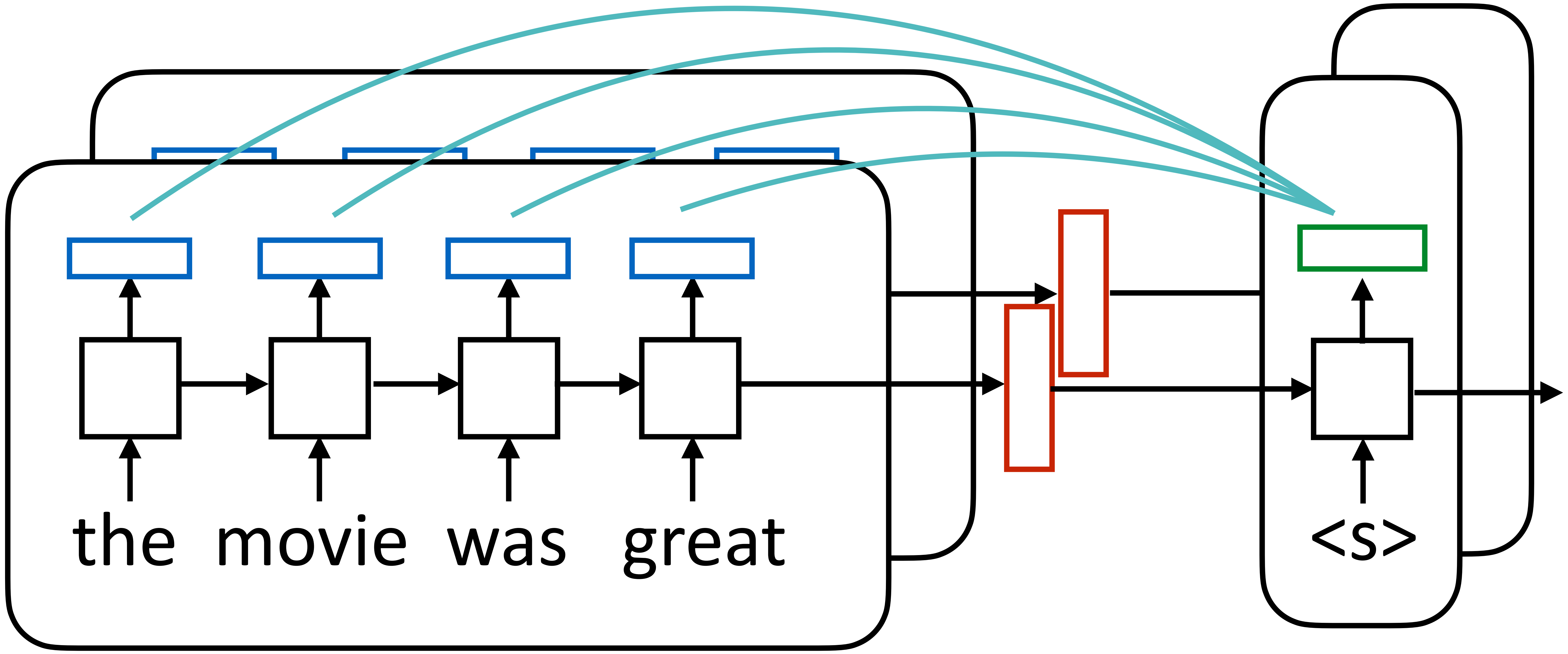
c = batch size x hidden size

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

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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sentence outputs:
batch size x hidden size

attention scores = batch size x sentence length

c = batch size x hidden size $\quad c_i = \sum_j \alpha_{ij} h_j$

- 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)

Luong et al. (2015)
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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)
- Summarization/headline generation: bigram recall from 11% -> 15%
- Semantic parsing: ~30% accuracy -> 70+% accuracy on Geoquery

Luong et al. (2015)
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

Jean et al. (2015), Luong et al. (2015)

Unknown Words

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1

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- Want to be able to copy named entities like Pont-de-Buis

Jean et al. (2015), Luong et al. (2015)

Unknown Words

- Want to be able to copy named entities like Pont-de-Buis

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

from attention

from RNN
hidden state

Jean et al. (2015), Luong et al. (2015)

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

from attention

from RNN hidden state

- Still can only generate from the vocabulary

Jean et al. (2015), Luong et al. (2015)

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 $\longrightarrow$ *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 $\longrightarrow$ *police arrested two*

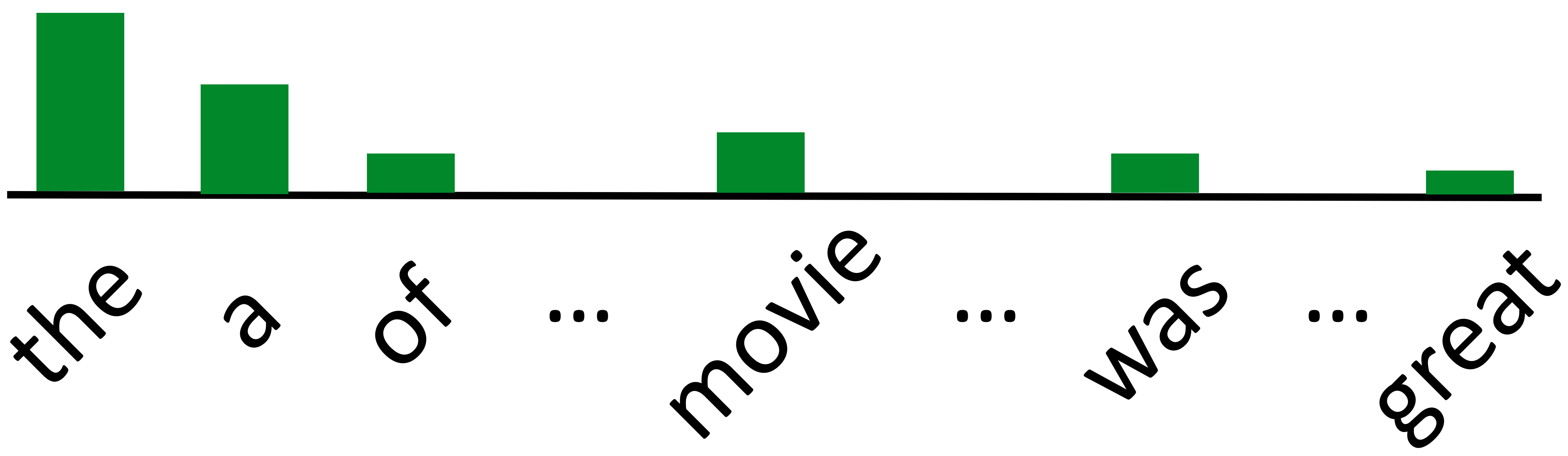
- Predicting from a fixed vocabulary doesn't make sense here

Output Space

- Let $[x_1, \ldots, x_n]$ 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

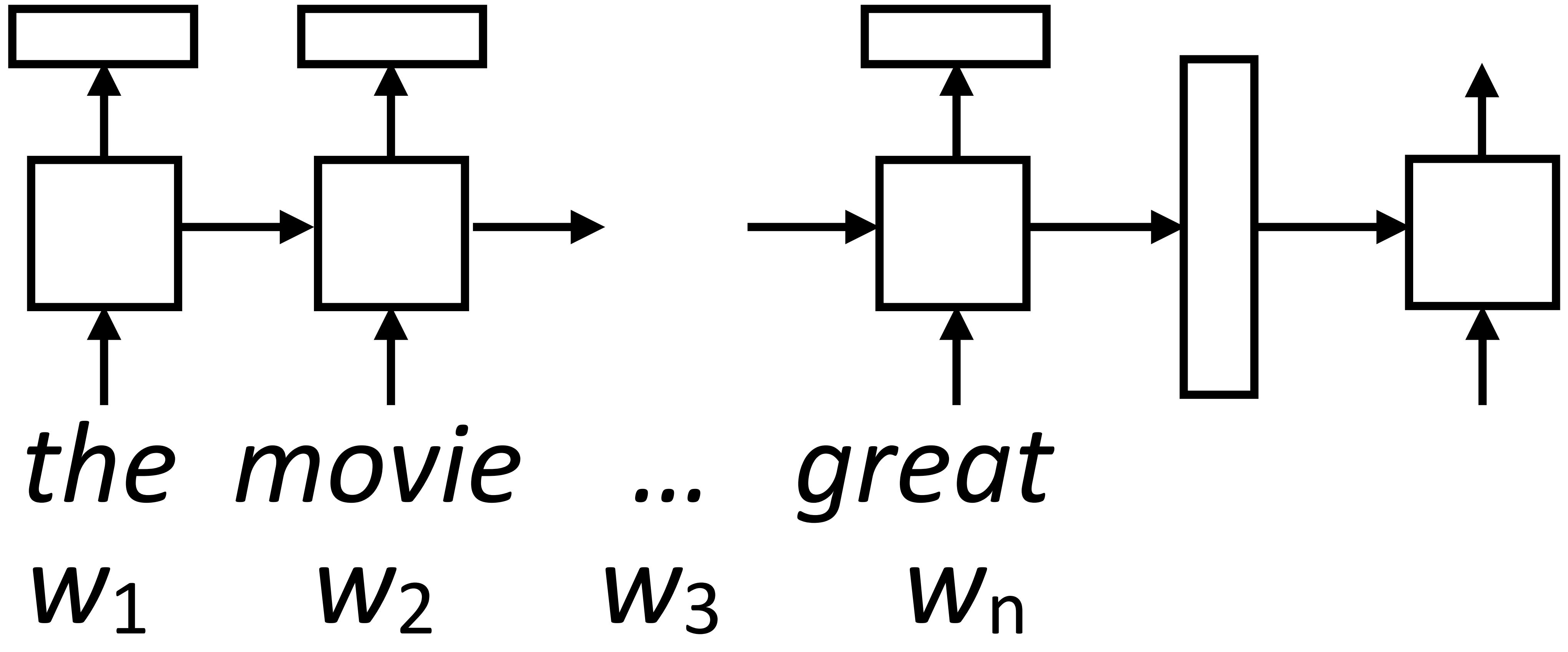
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W[c_i; \bar{h}_i])$$

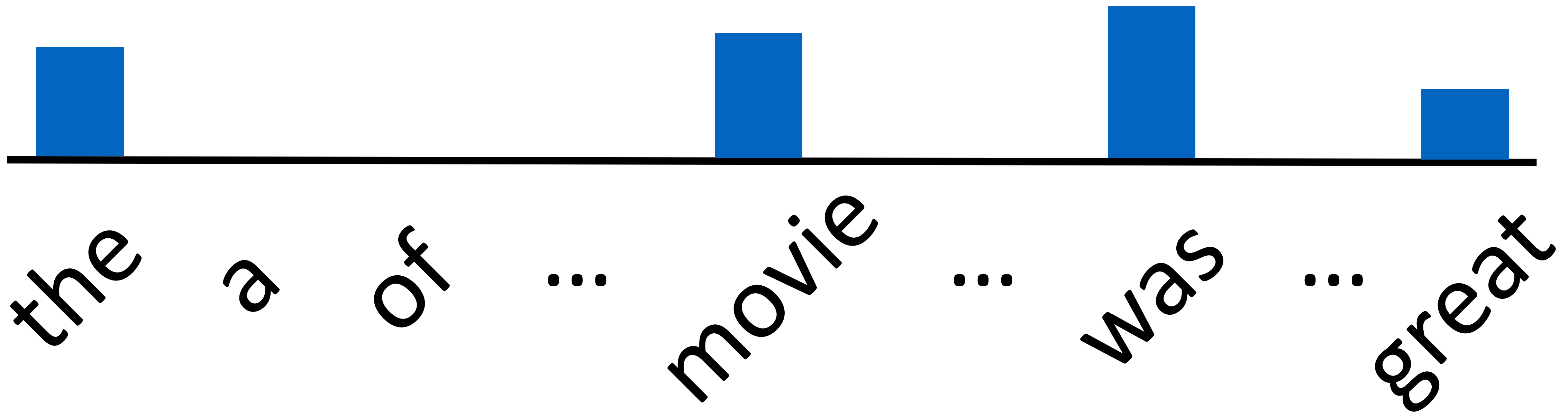


- Standard decoder (P_{vocab}): softmax over vocabulary, all words get >0 prob

- Pointer network: predict from *source words* instead of *target vocab*

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



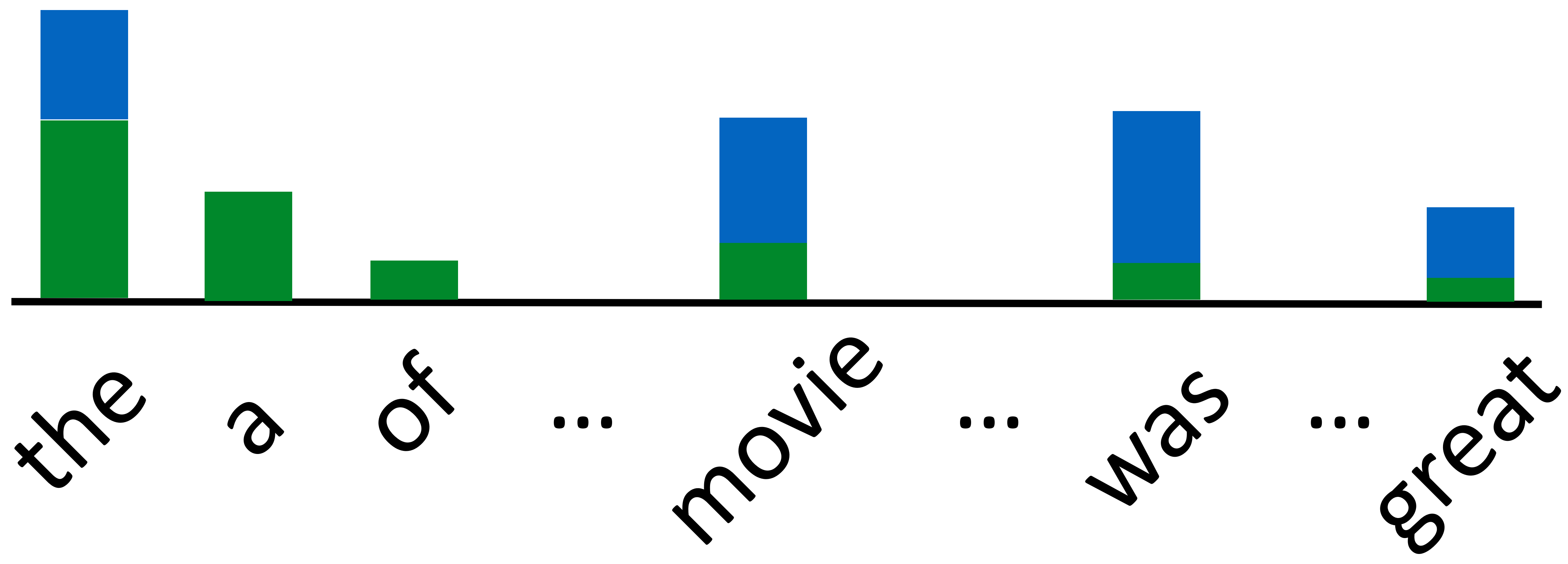


Pointer Generator Mixture Models

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

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

- Predict *P*(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



Copying

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Copying

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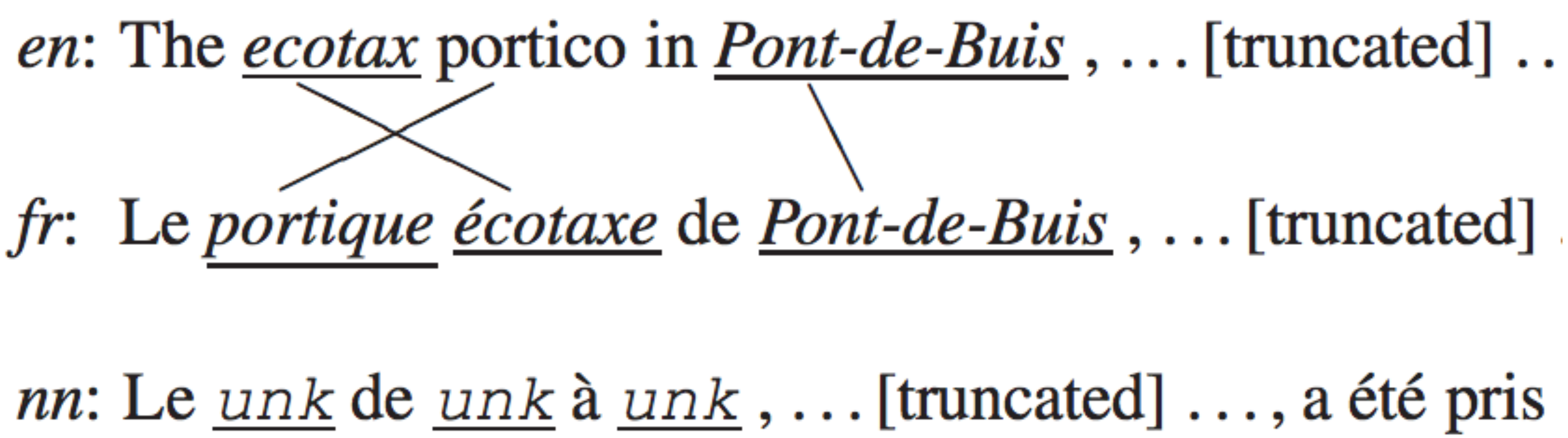
nn: Le unk de unk à unk , . . . [truncated] . . . , a été pris

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

Copying



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

the
a
…
zebra

Pont-de-Buis
ecotax

Copying

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$$P(y_i = w|\mathbf{x}, y_1, \ldots, y_{i-1}) \propto \begin{cases} \exp W_w[c_i; \bar{h}_i] & \text{if } w \text{ in vocab} \\ h_j^\top V \bar{h}_i & \text{if } w = x_j \end{cases}$$

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

$$\left\{ \begin{array}{l} \text{the} \\ \text{a} \\ \ldots \\ \text{zebra} \\ \hline \text{Pont-de-Buis} \\ \text{ecotax} \end{array} \right\}$$

$$P(y_i = w | \mathbf{x}, y_1, \ldots, y_{i-1}) \propto \begin{cases} \exp W_w [c_i; \bar{h}_i] & \text{if } w \text{ in vocab} \\ h_j^\top V \bar{h}_i & \text{if } w = x_j \end{cases}$$

- Bilinear function of input representation + output hidden state

Results

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

Jia and Liang (2016)

Results

	GEO	ATIS
No Copying	74.6	69.9
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- For semantic parsing, copying tokens from the input (texas) can be very useful

Jia and Liang (2016)

Results

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

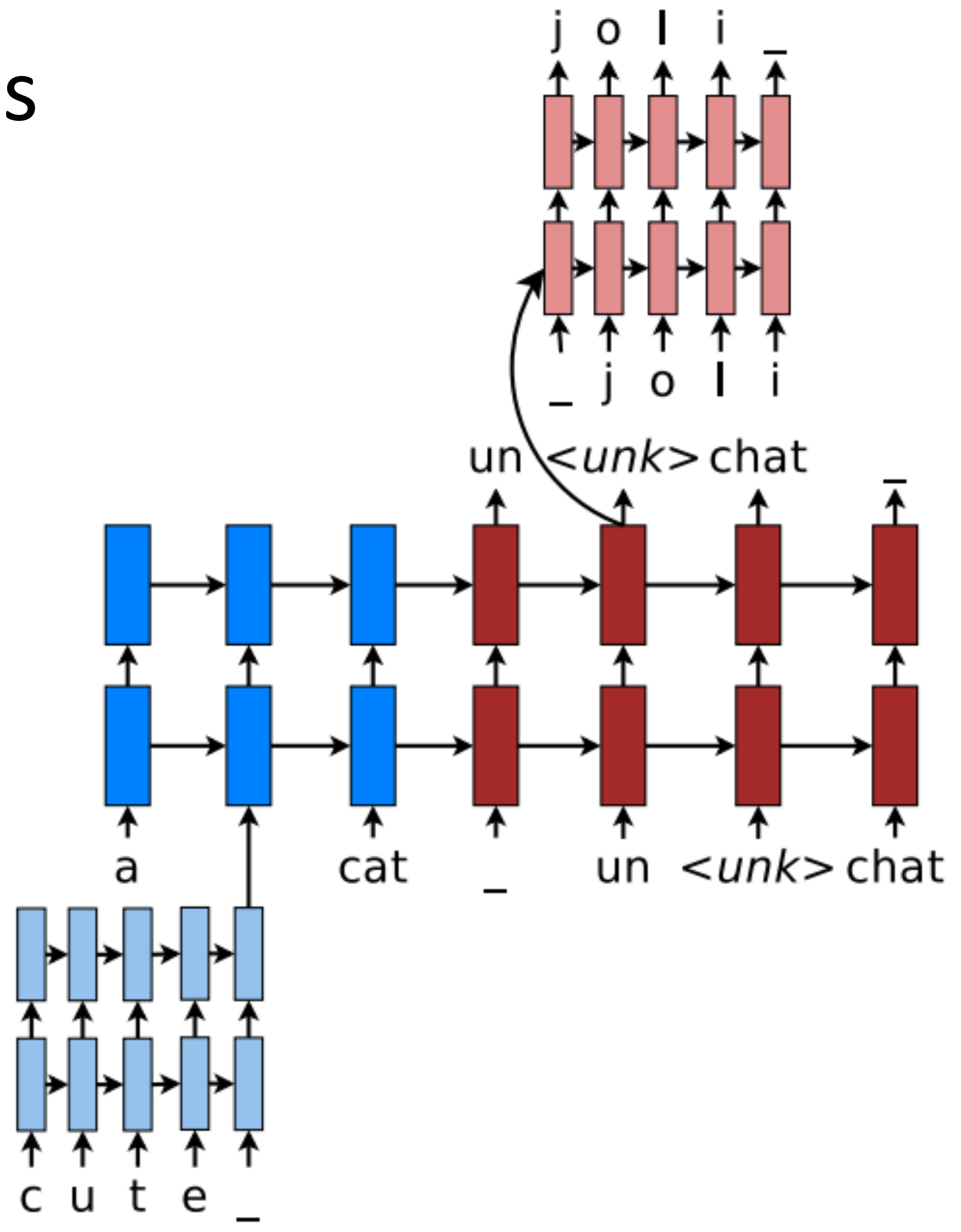
- For semantic parsing, copying tokens from the input (texas) can be very useful

- In many settings, attention can roughly do the same things as copying

Jia and Liang (2016)

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

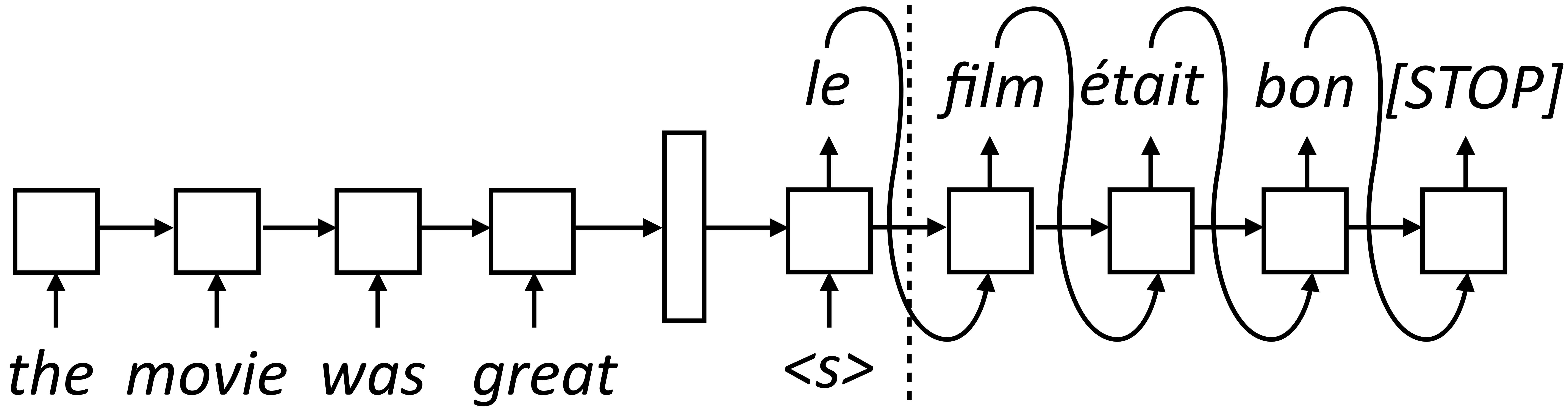


Luong et al. (2016)

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**

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

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

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%

Stahlberg and Byrne (2019)

“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

Stahlberg and Byrne (2019)

Sampling

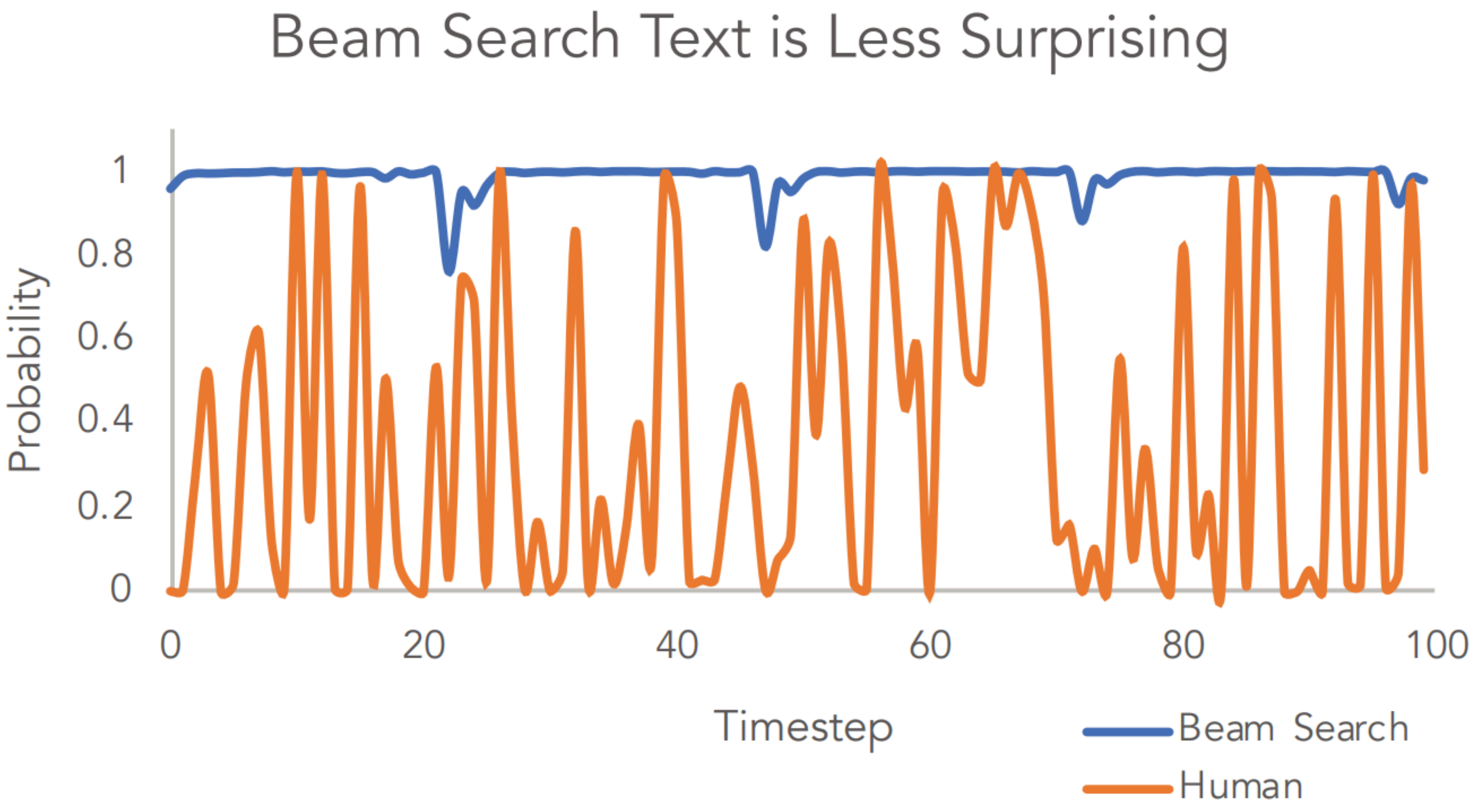
- Beam search may give many similar sequences, and these actually may be *too close* to the optimal. Can sample instead:

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

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

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

Beam Search vs. Sampling



Holtzman et al. (2019)

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 ..."

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

Holtzman et al. (2019)

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

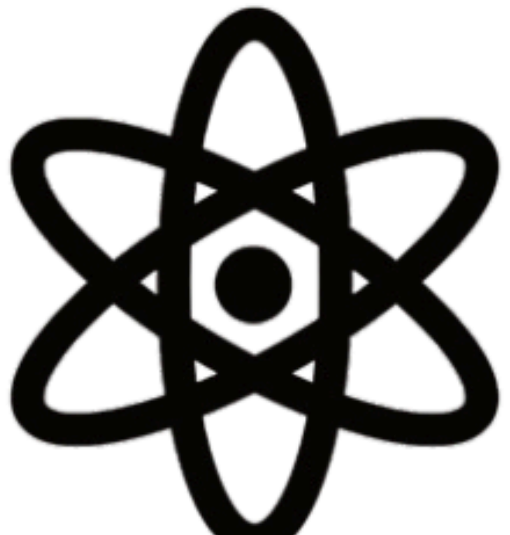
An unprecedented number of mostly young whales have become stranded on the West Australian coast since 2008.

Beam Search, *b*=16

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.

Pure Sampling

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.



Nucleus, *p*=0.95

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

Less constrained ⟷ More constrained

Unconditioned sampling/ "story generation"

Dialogue

Translation

Summarization

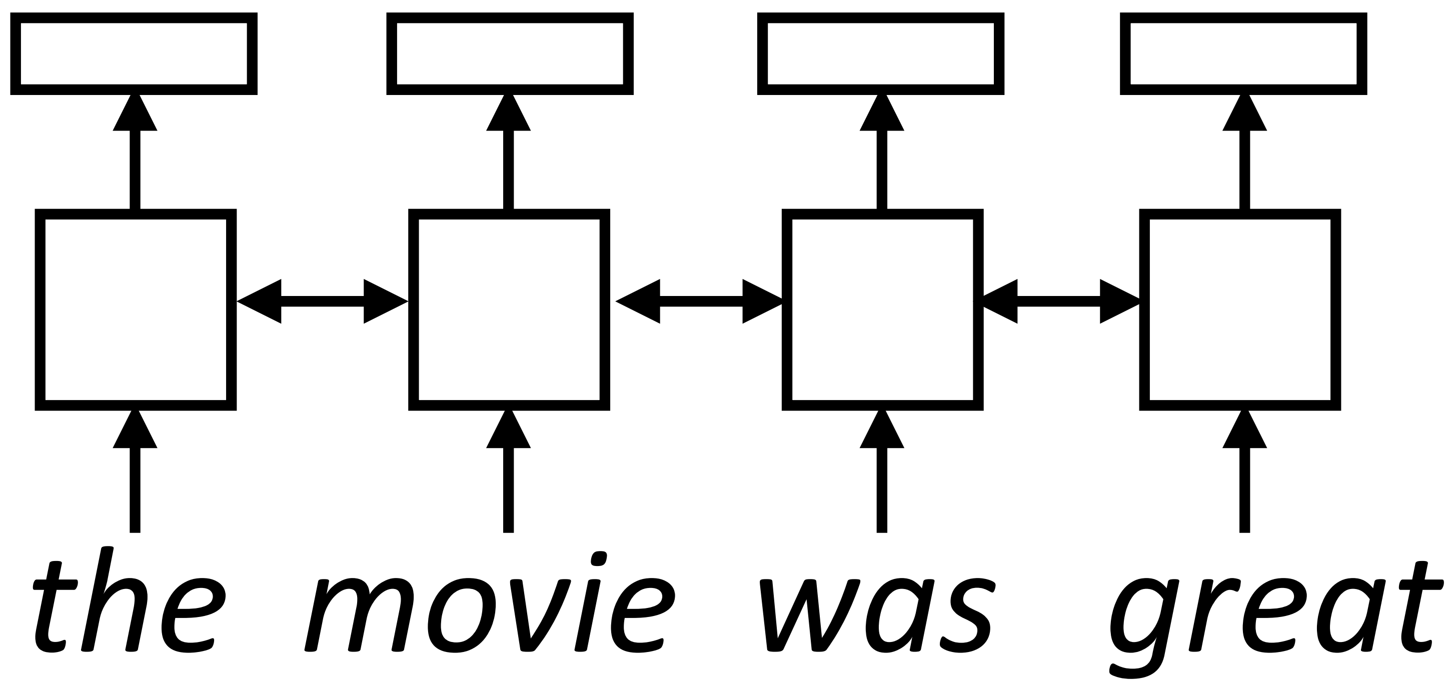
Data-to-text

Text-to-code

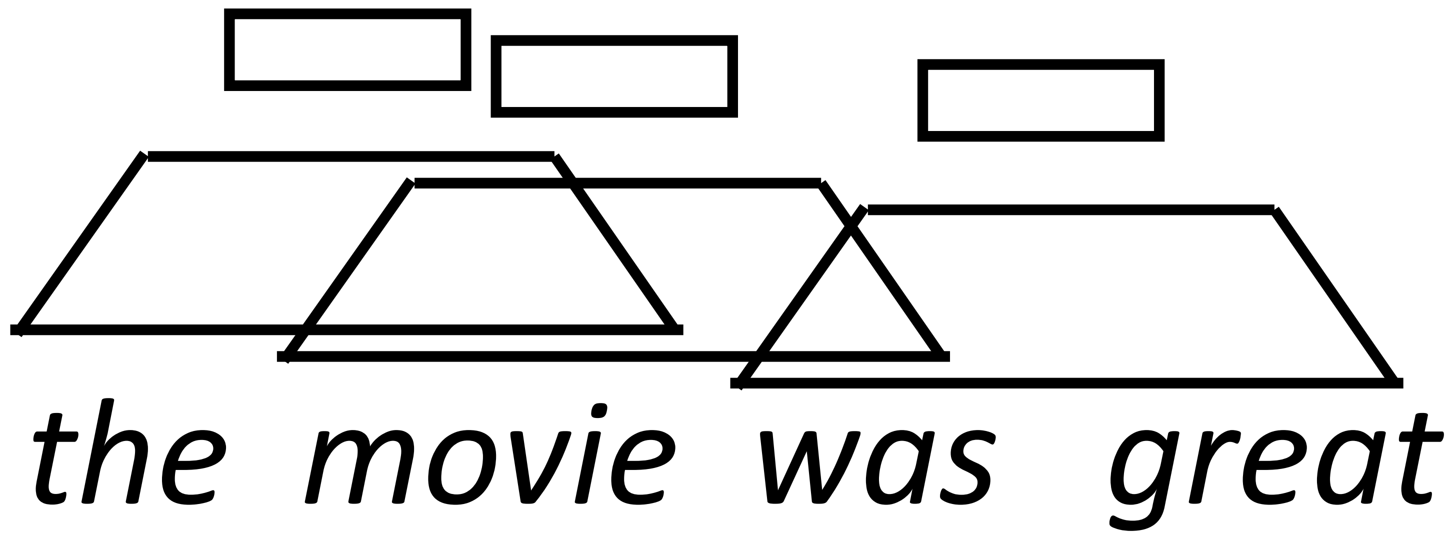
Transformers

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

Vaswani et al. (2017)

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

Vaswani et al. (2017)

Self-Attention

- Want:

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

- LSTMs/CNNs: tend to look at local context

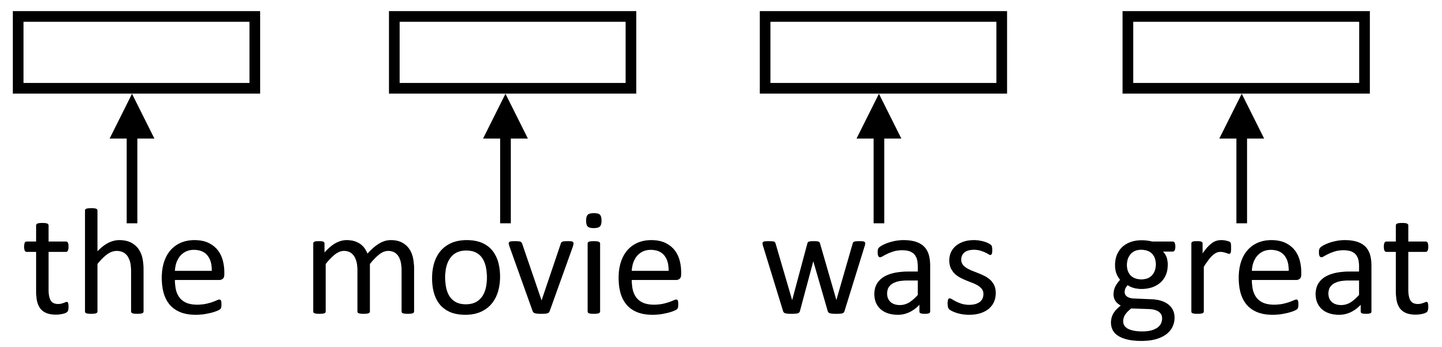
The ballerina is very excited that she will dance in the show.

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

Vaswani et al. (2017)

Self-Attention

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



Vaswani et al. (2017)

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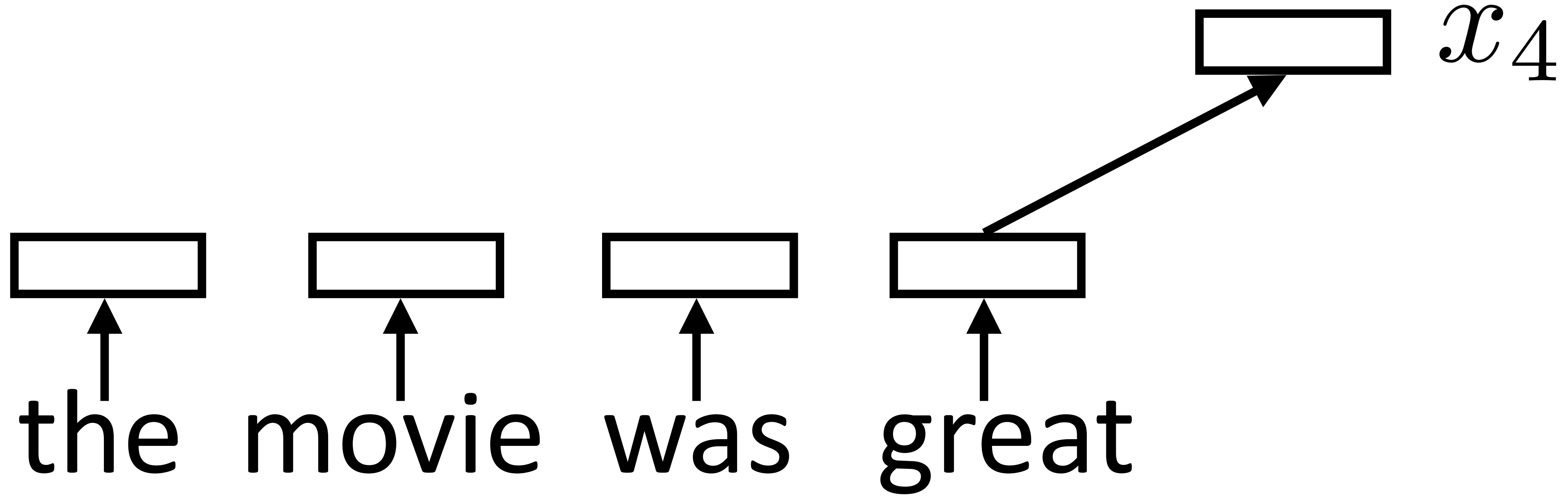

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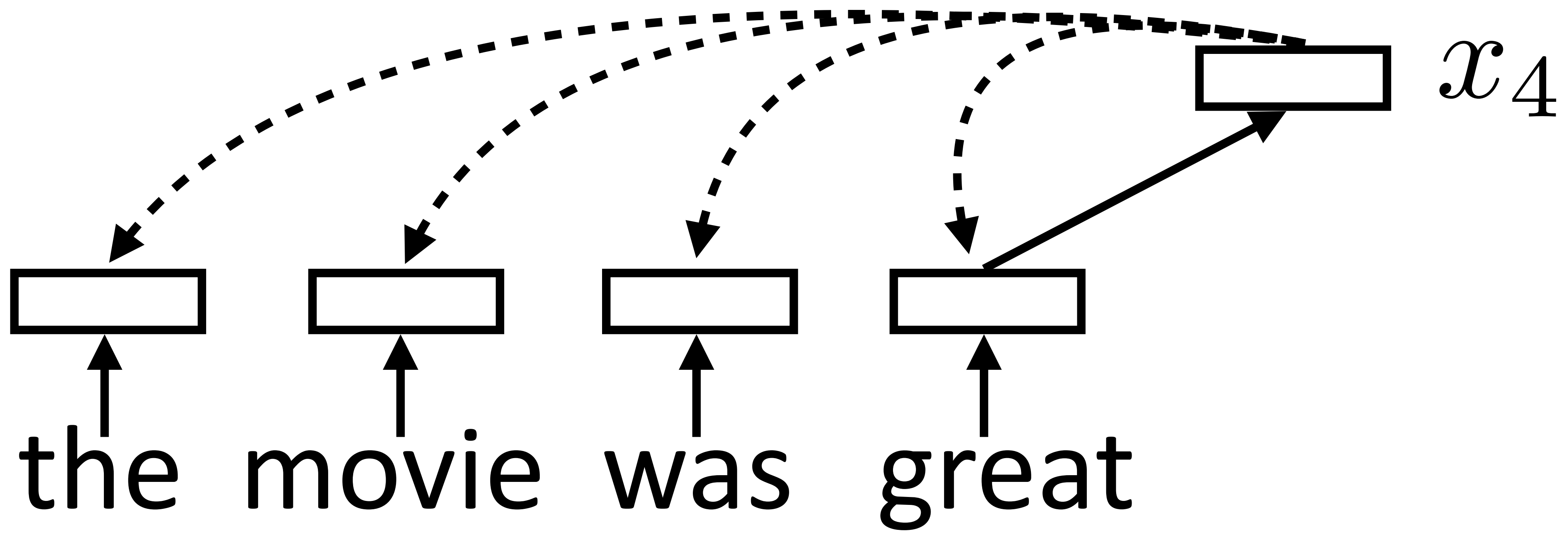

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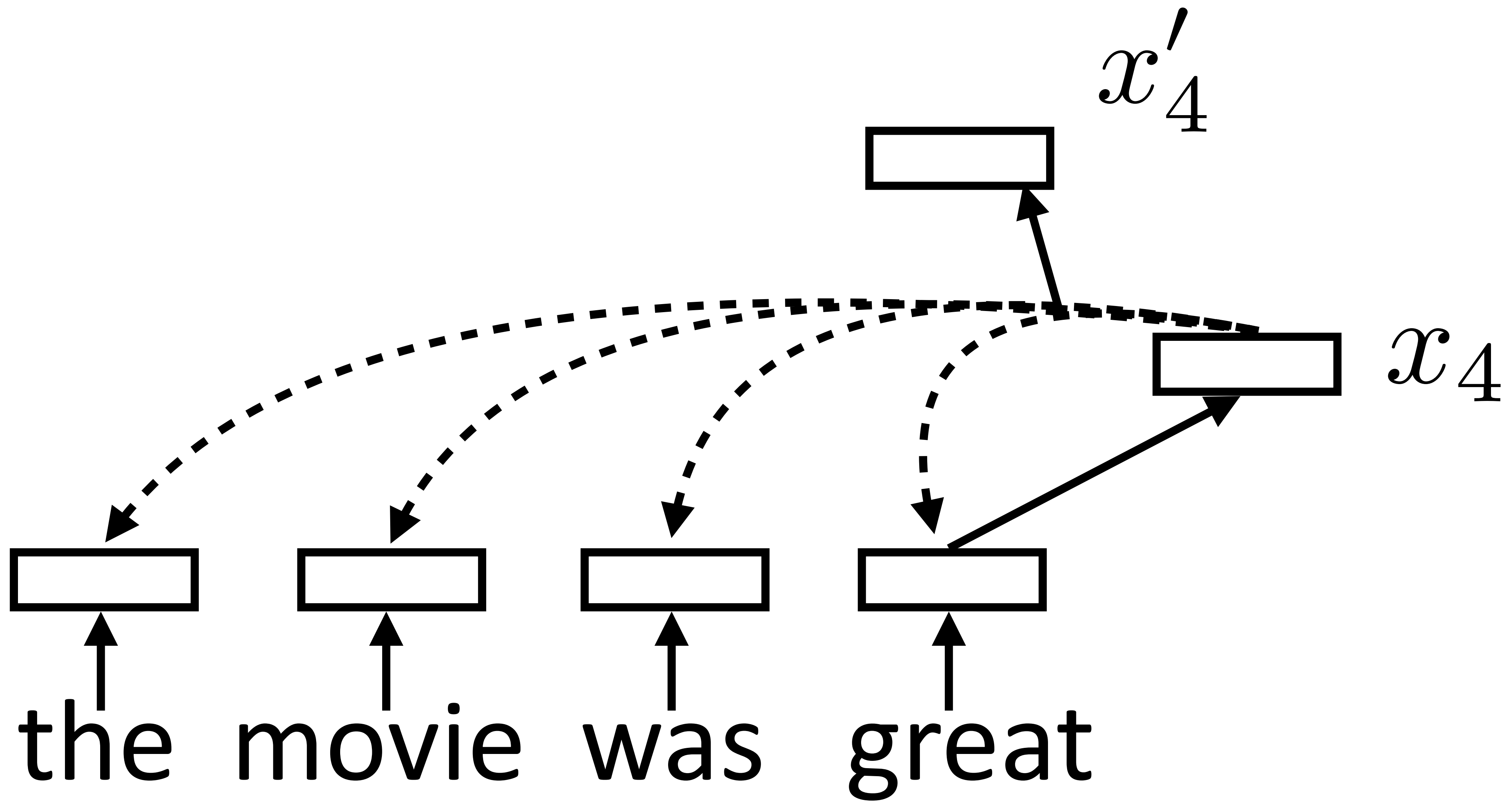
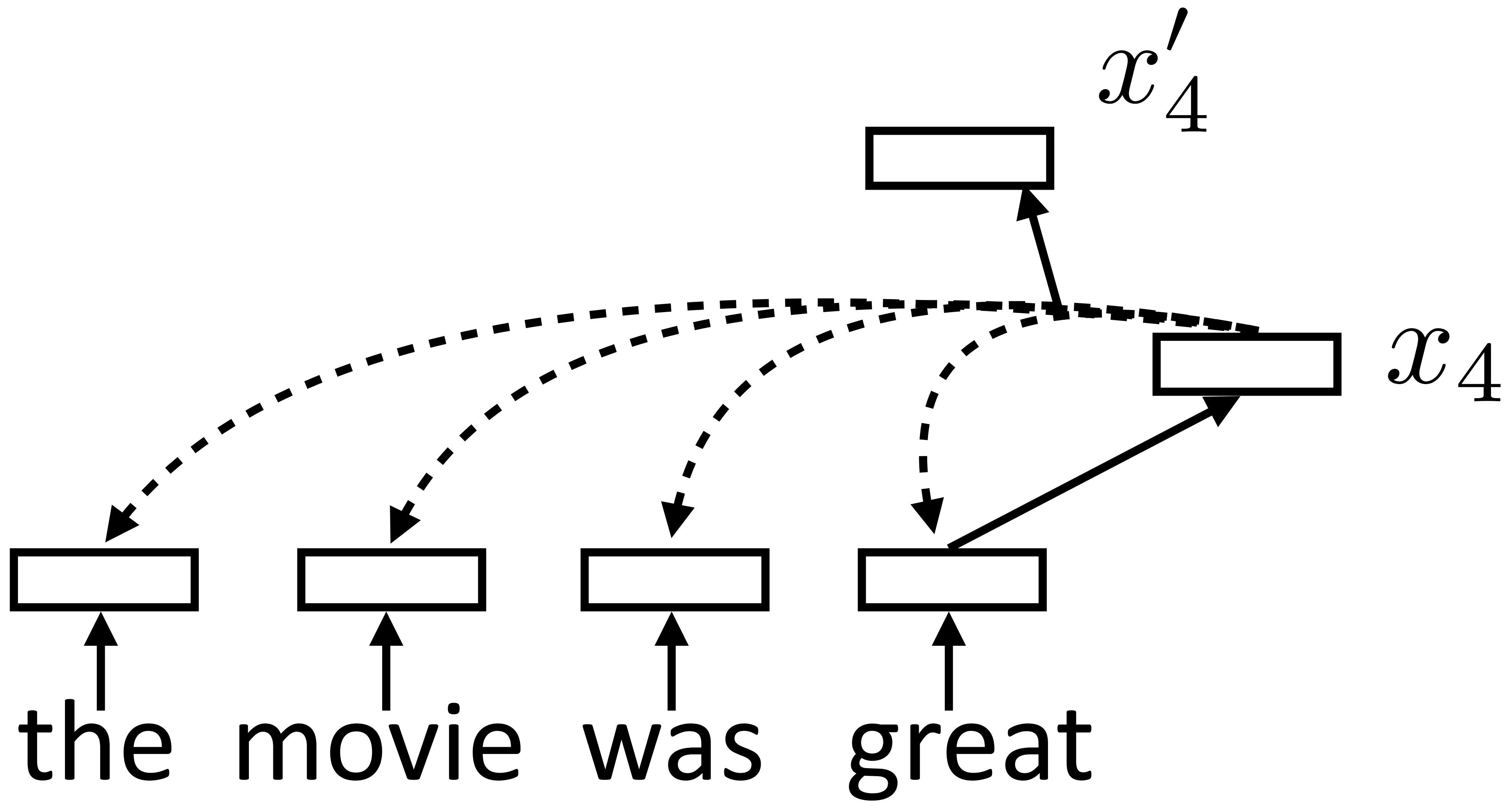


Vaswani et al. (2017)

Self-Attention

- Each word forms a "query" which then computes attention over each word

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



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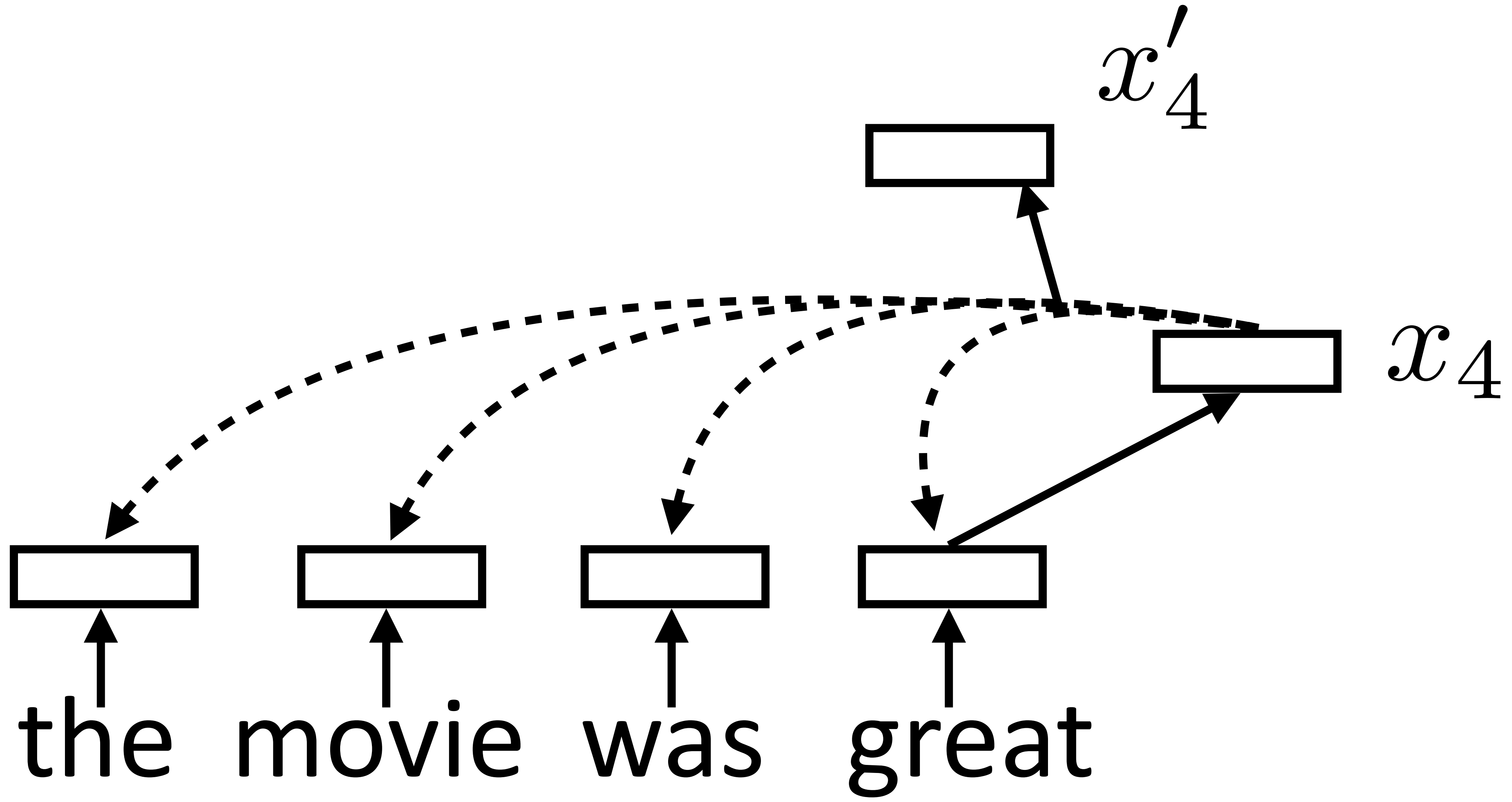
$$\alpha_{i,j} = \text{softmax}(x_i^\top x_j) \quad \text{scalar}$$

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



Vaswani et al. (2017)

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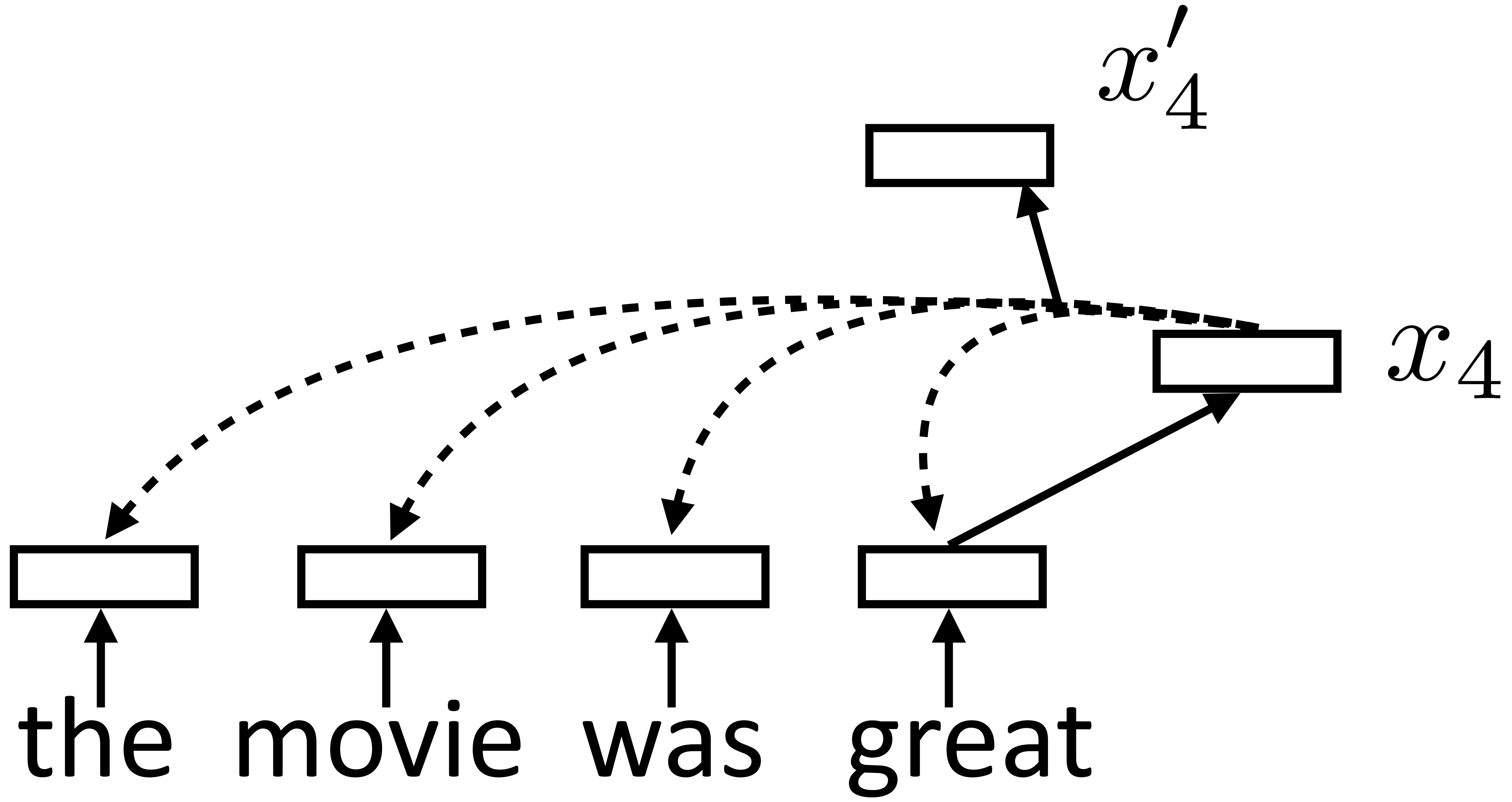

- Multiple "heads" analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

Vaswani et al. (2017)

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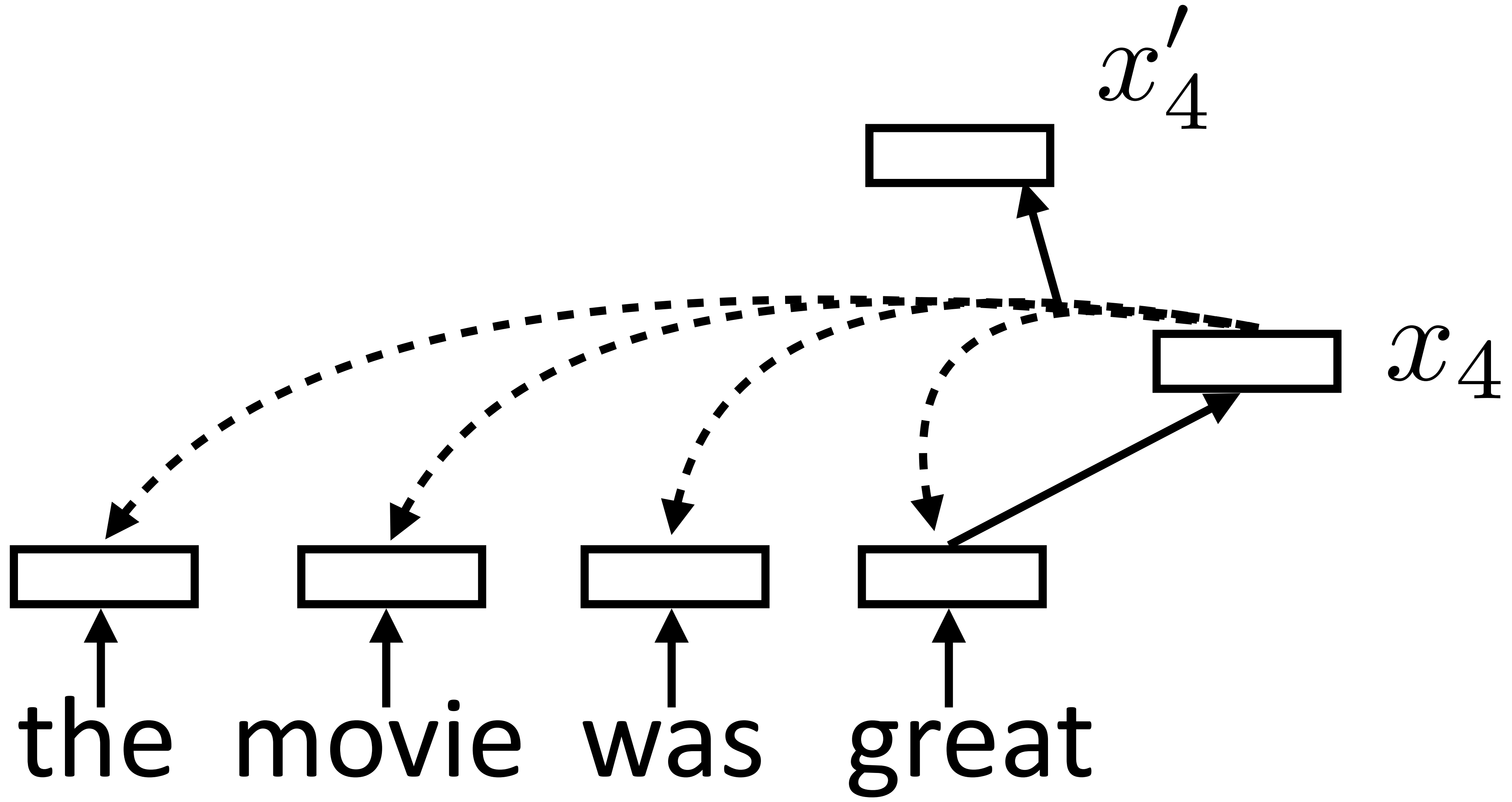

- Multiple "heads" analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

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

Vaswani et al. (2017)

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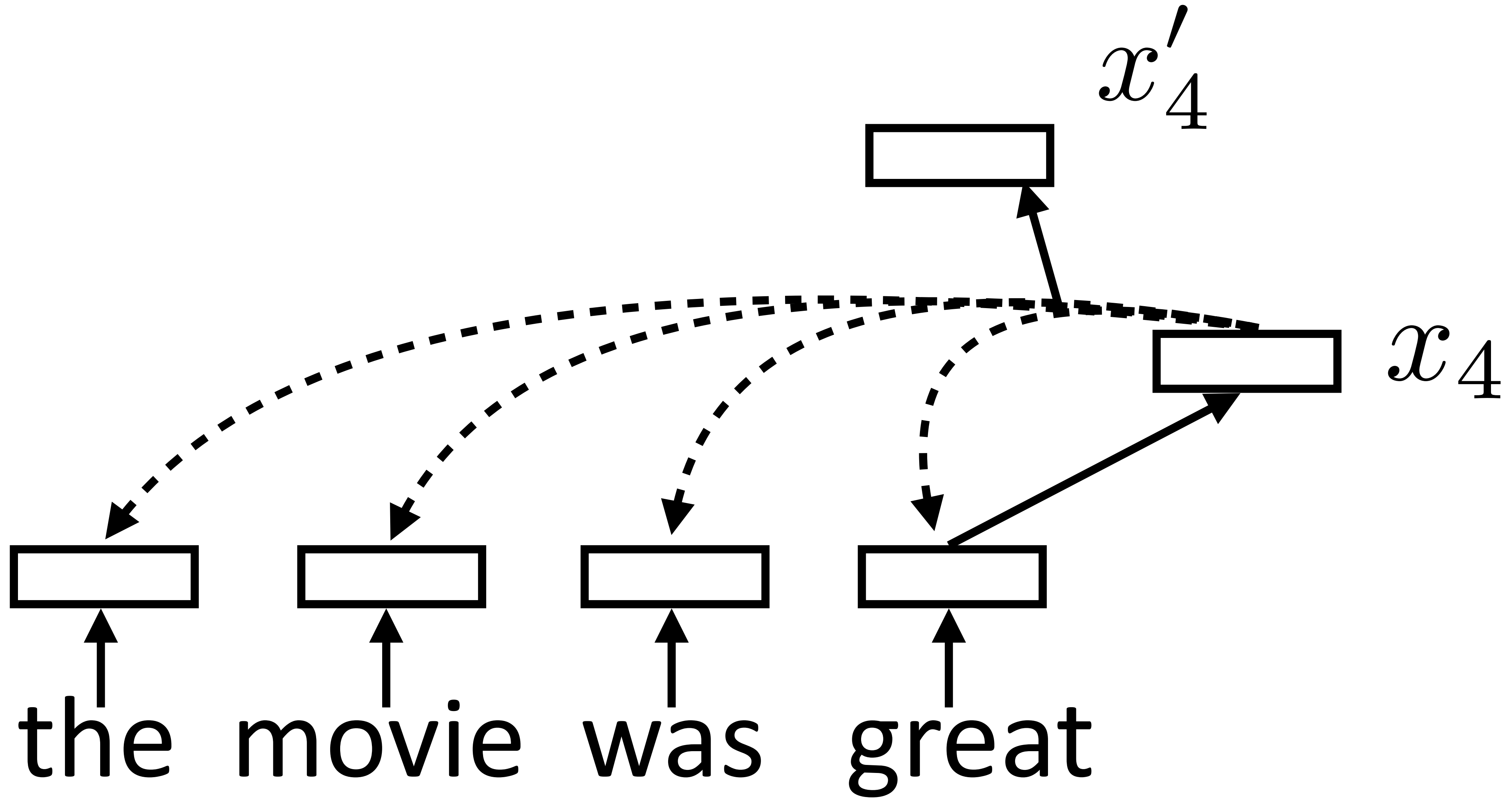

- Multiple "heads" analogous to different convolutional filters. Use parameters *W* W_k and V_k to get different attention values + transform vectors

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

Vaswani et al. (2017)

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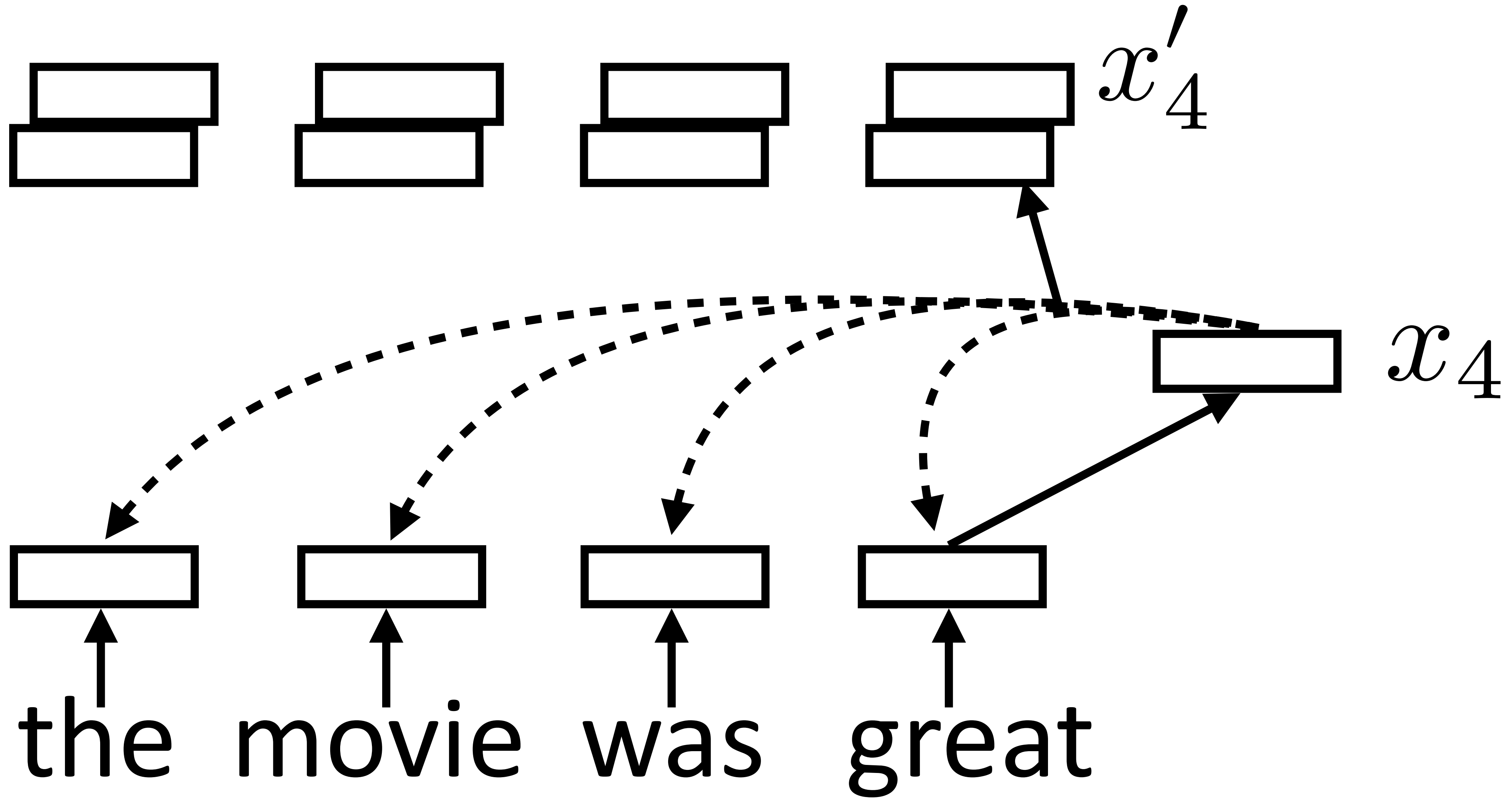

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Vaswani et al. (2017)

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

0	0.1	0	0	0	0	0	0	0.5	0	0.4	0

- 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

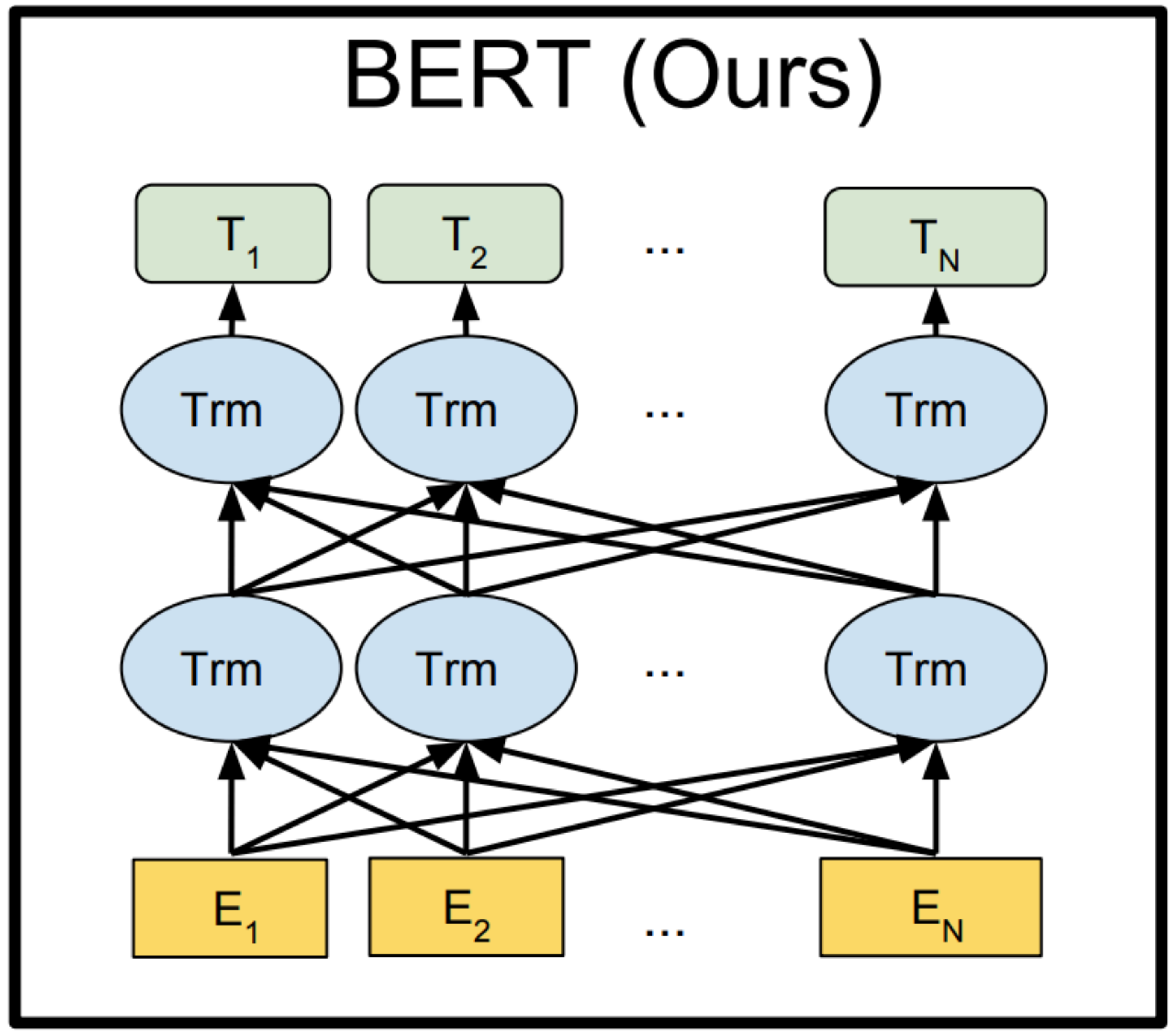
Vaswani et al. (2017)

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)

Takeaways

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- Explicitly copying input can be beneficial as well
- Transformers are strong models we'll come back to later