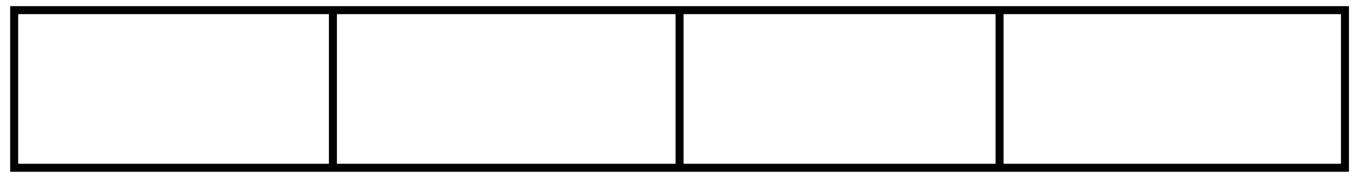
Lecture 11: Seq2Seq + Attention

Alan Ritter

(many slides from Greg Durrett)

Recall: CNNs vs. LSTMs



n x k

the movie was good

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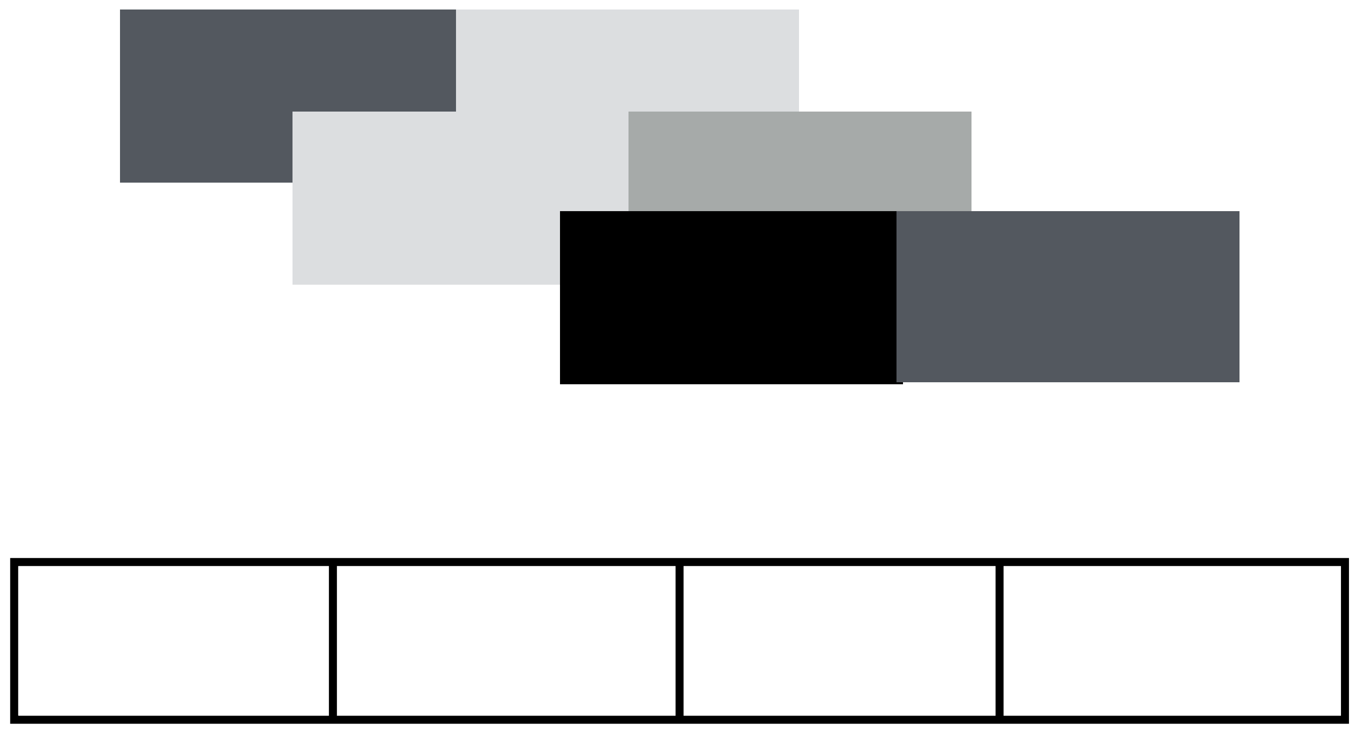

c filters,
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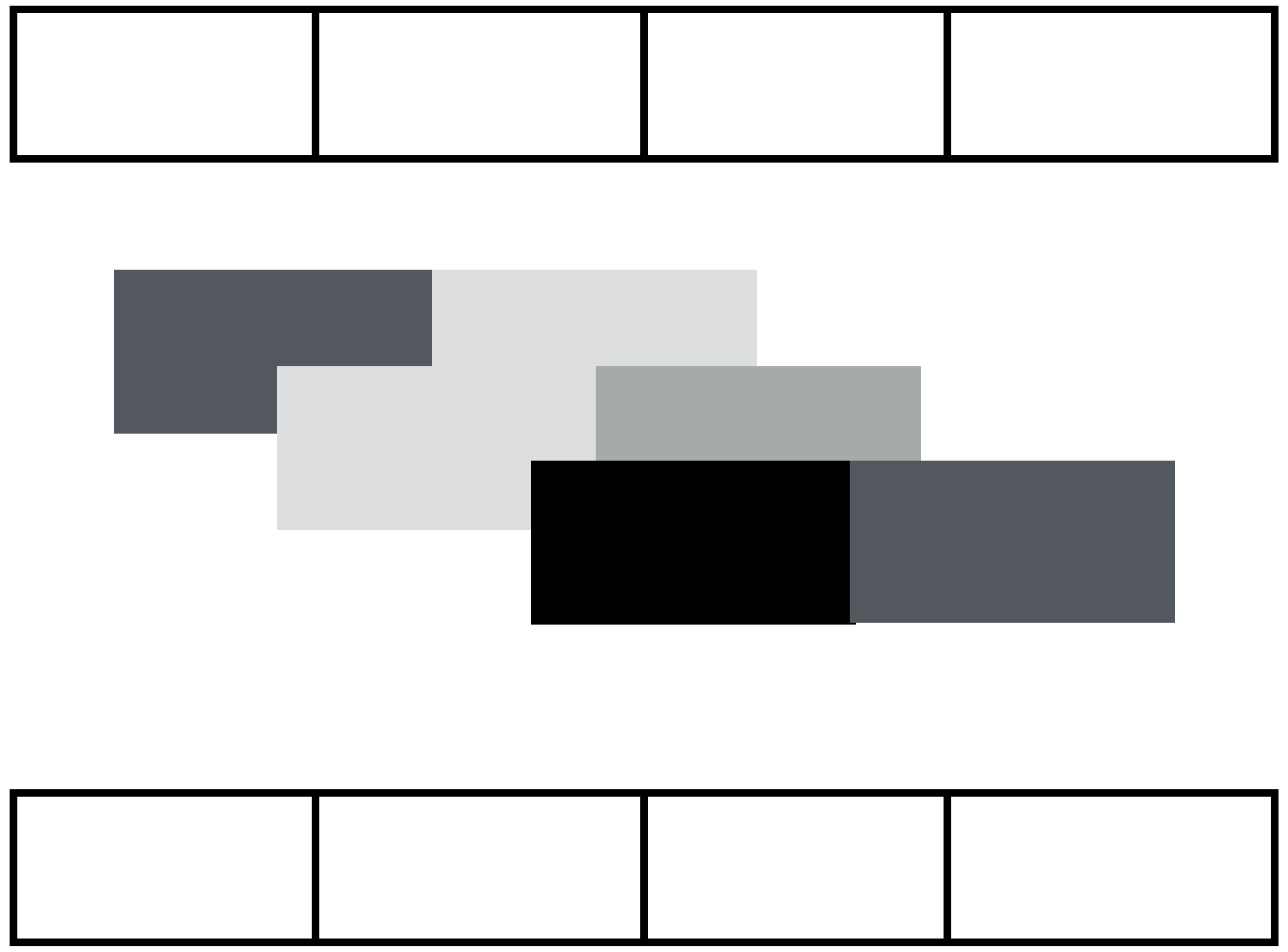

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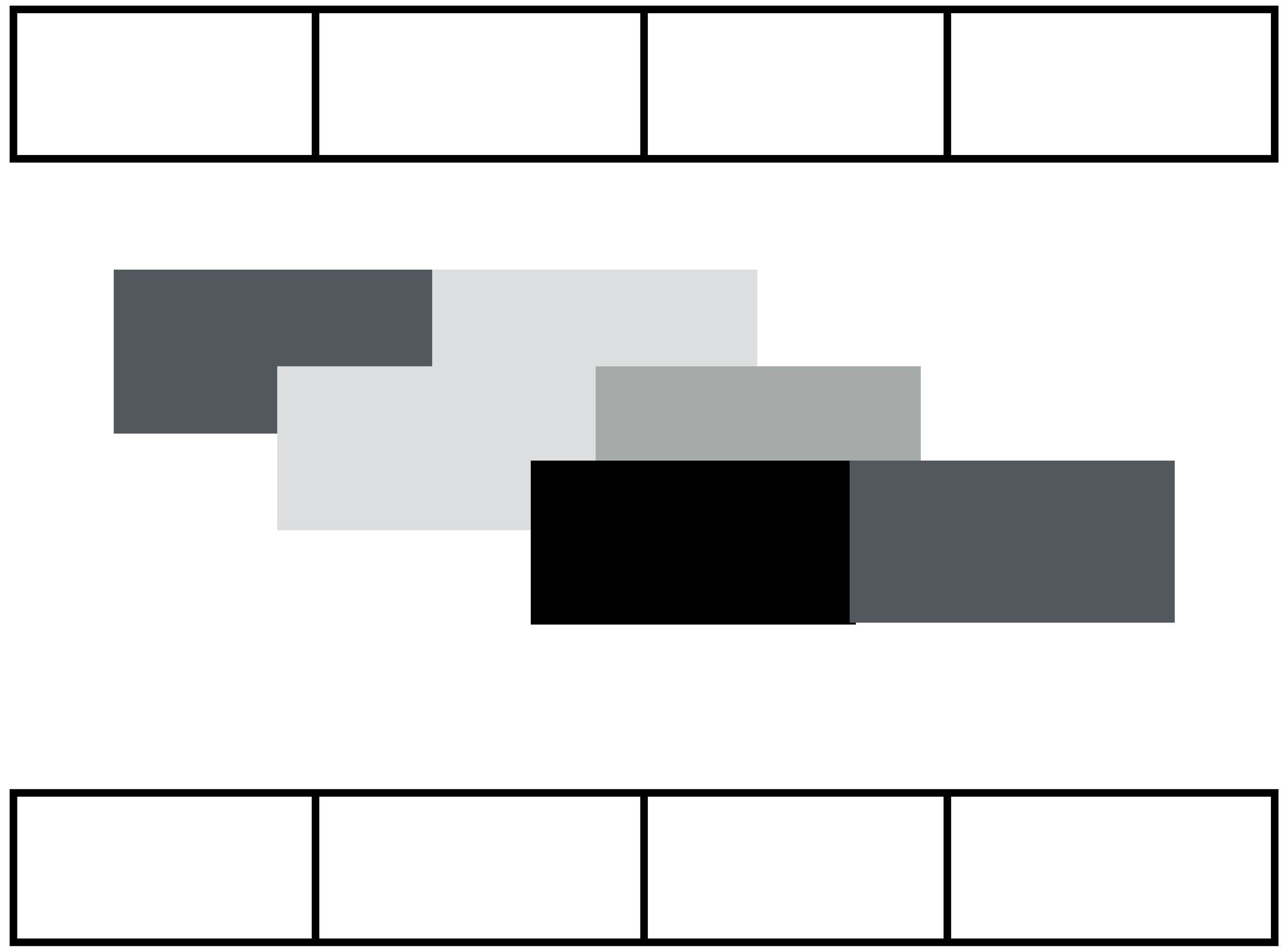

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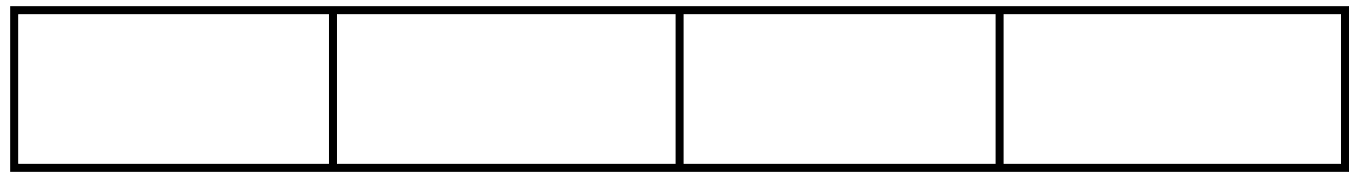

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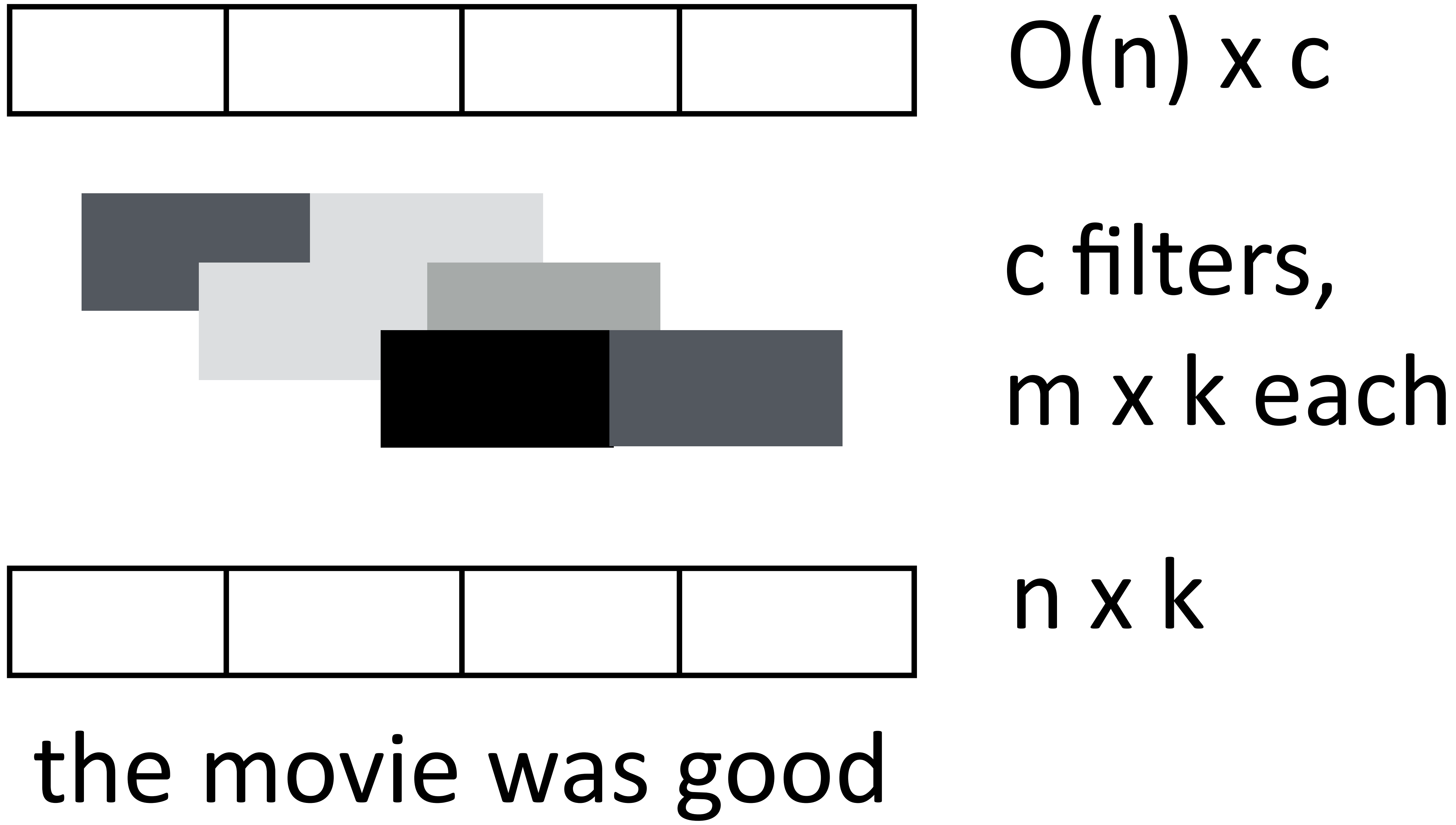

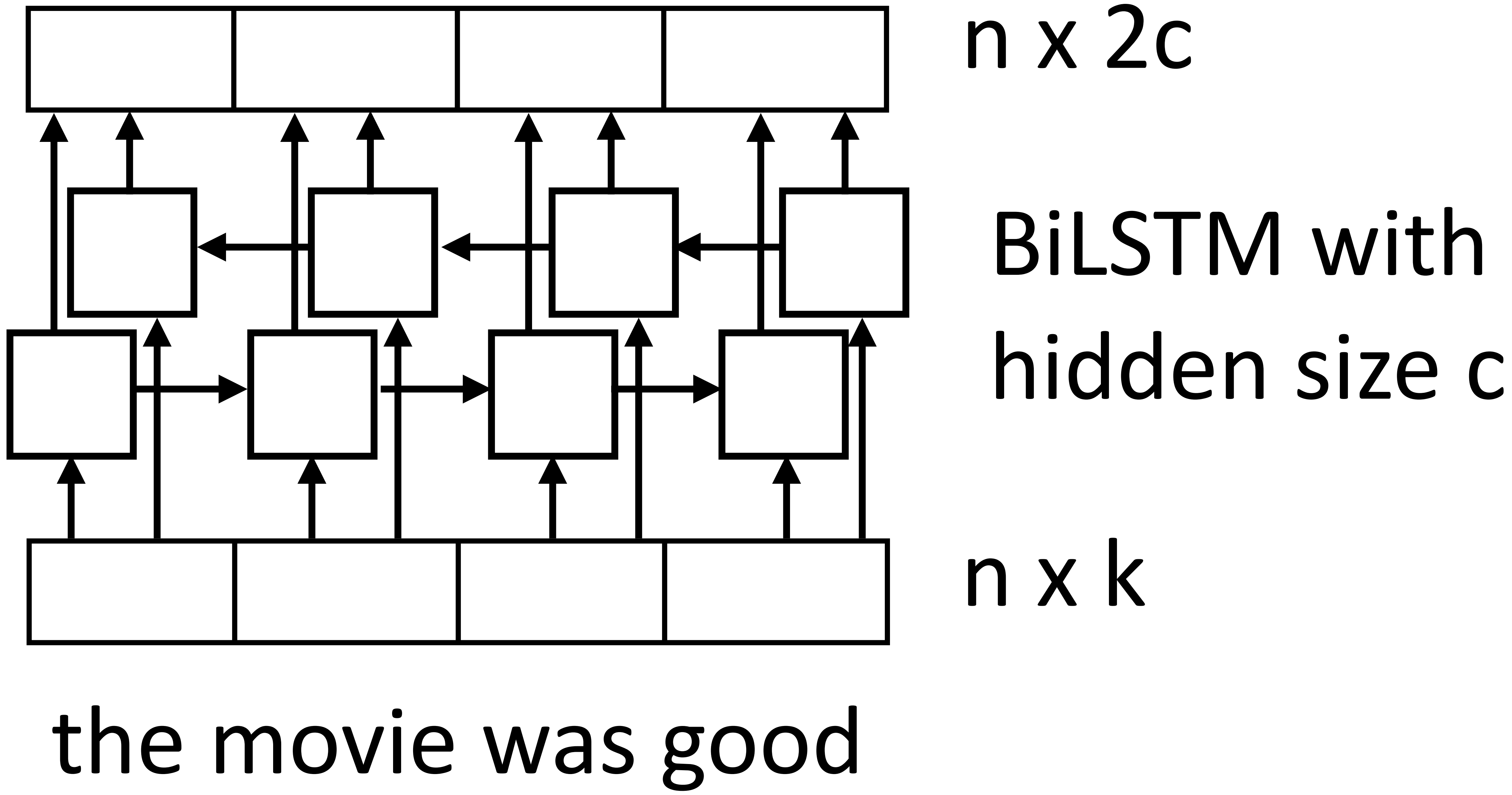

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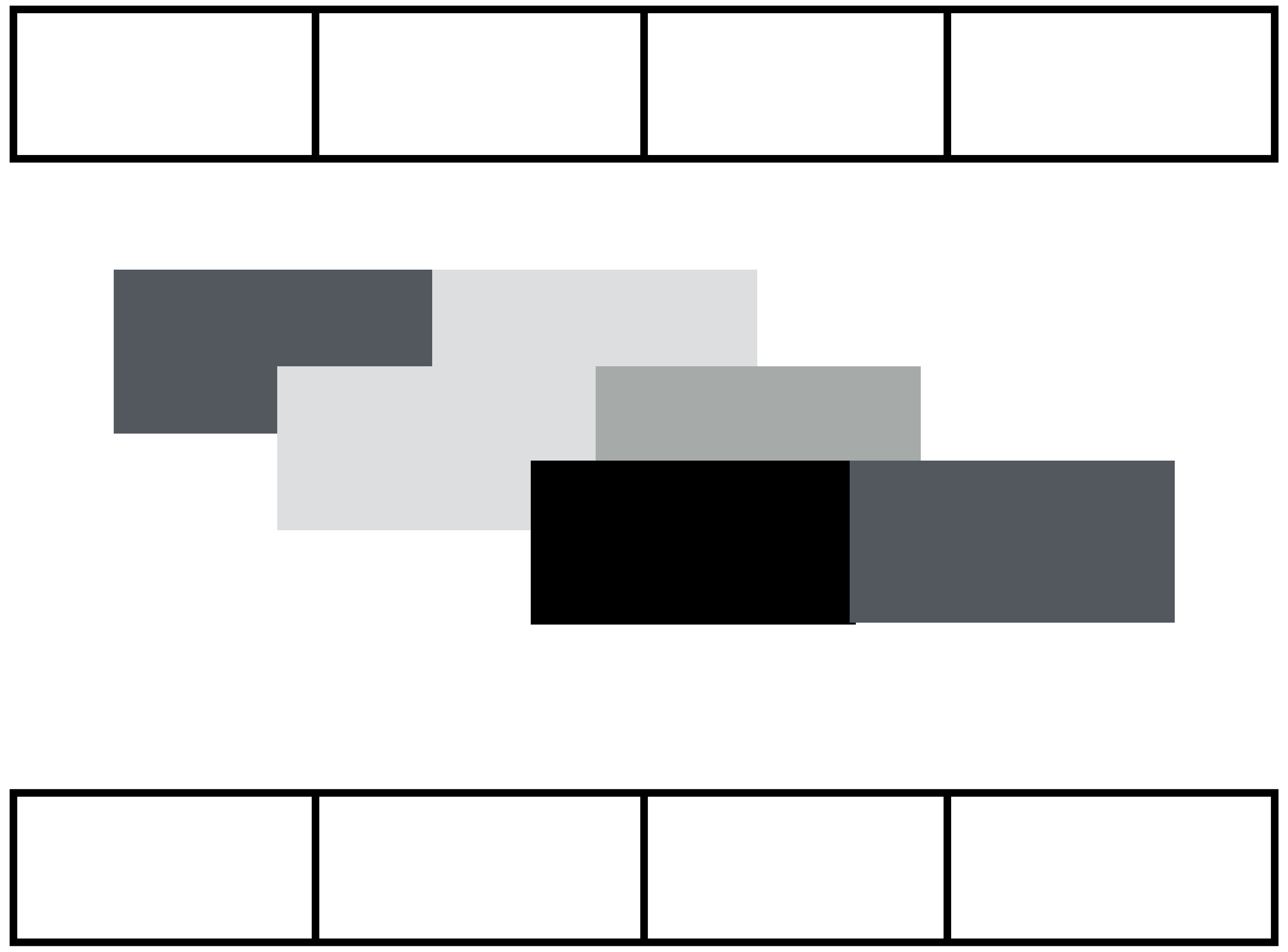
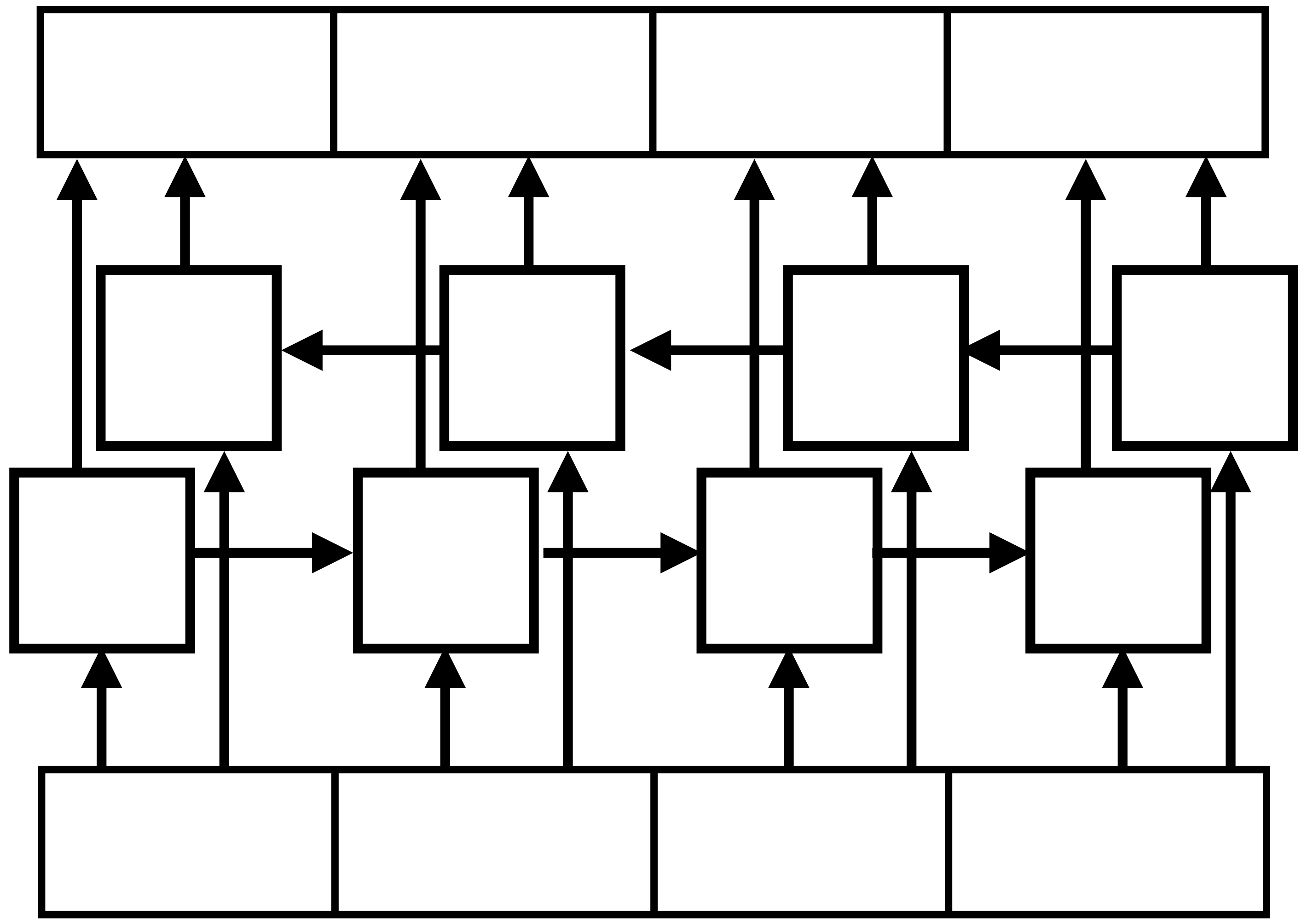
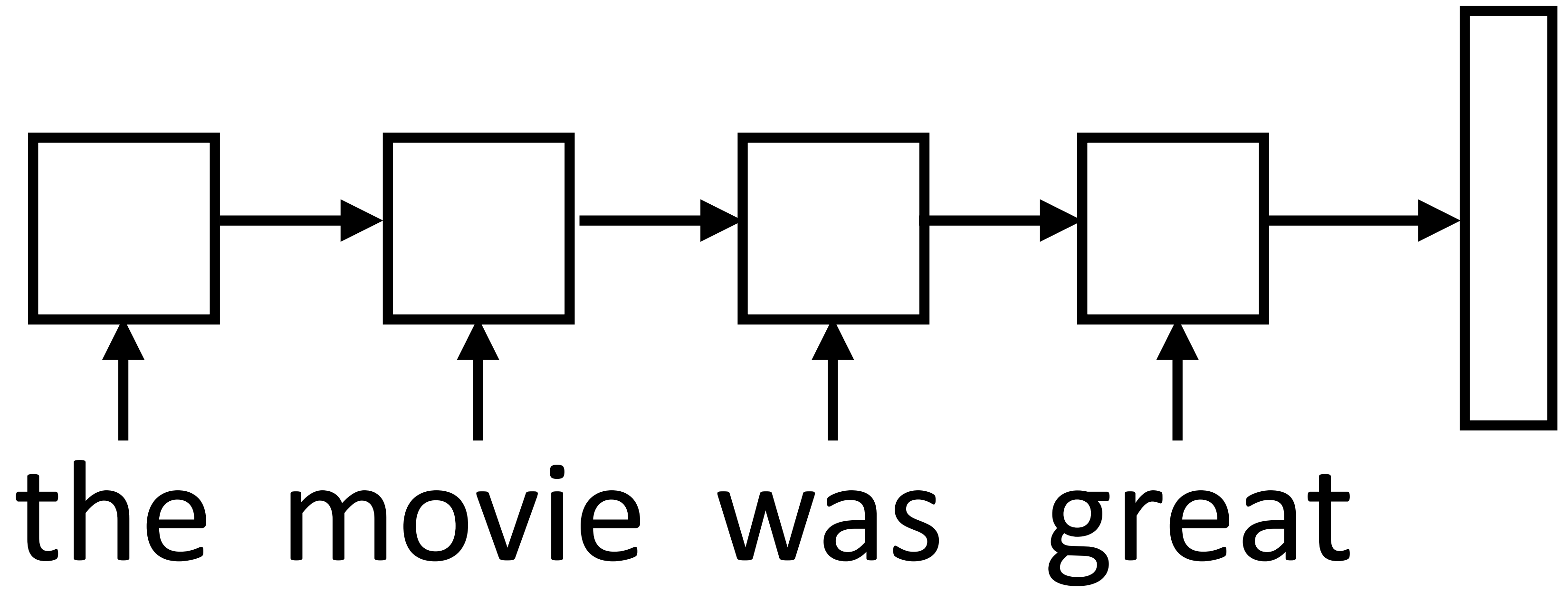




- Both LSTMs and convolutional layers transform the input using context
- LSTM: “globally” looks at the entire sentence (but local for many problems)
- CNN: local depending on filter width + number of layers

Encoder-Decoder

- Encode a sequence into a fixed-sized vector



Sutskever et al. (2014)

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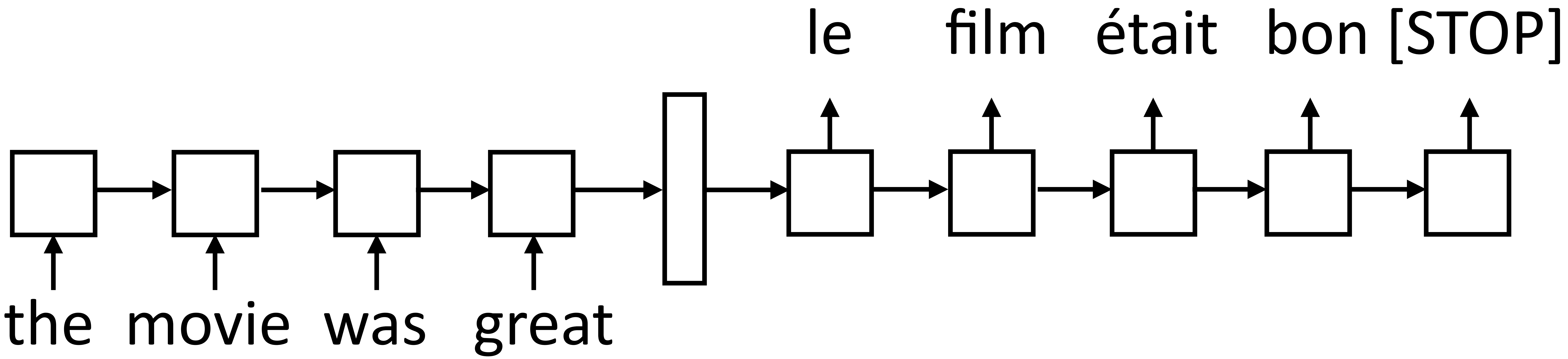
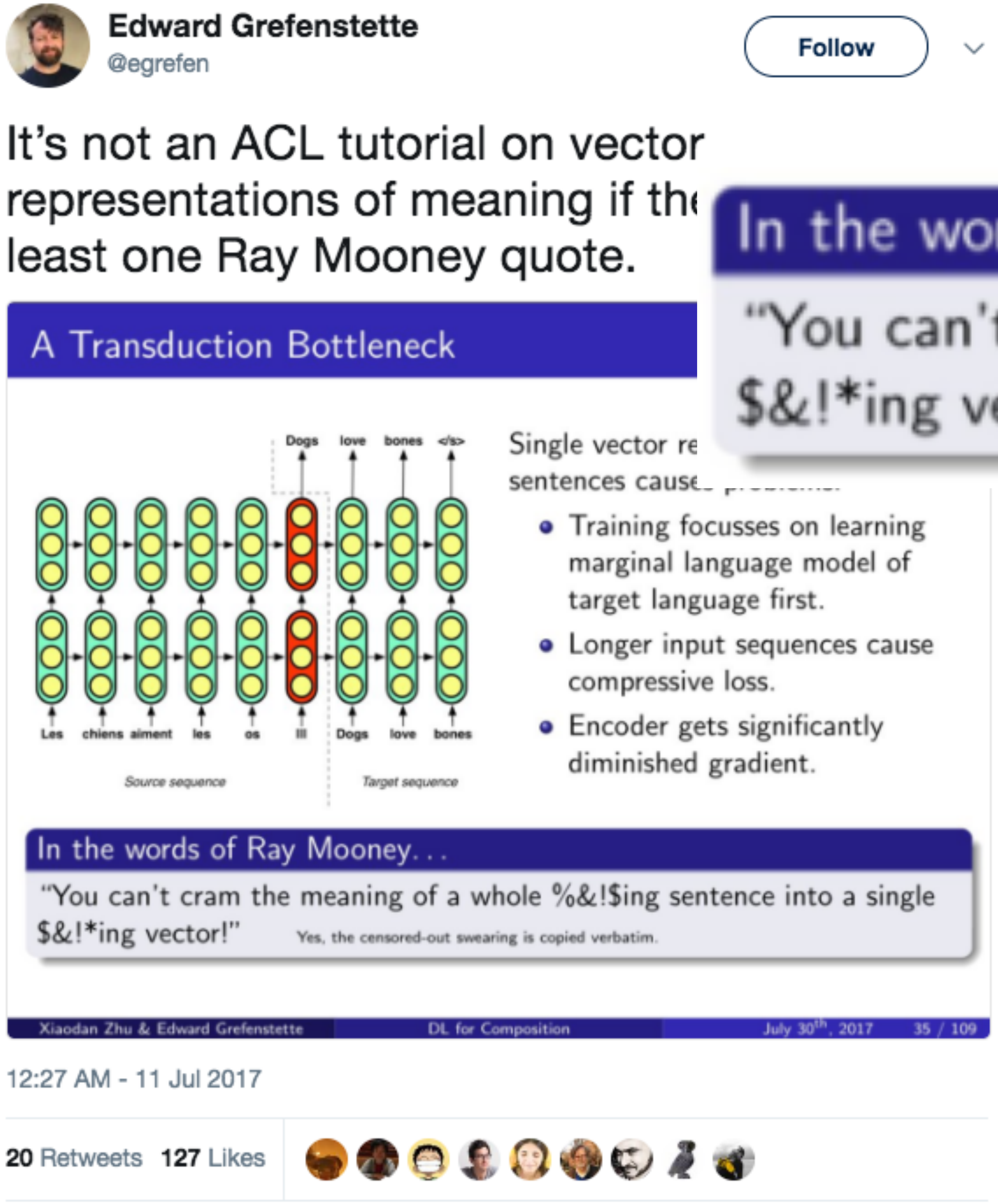


- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

Encoder-Decoder



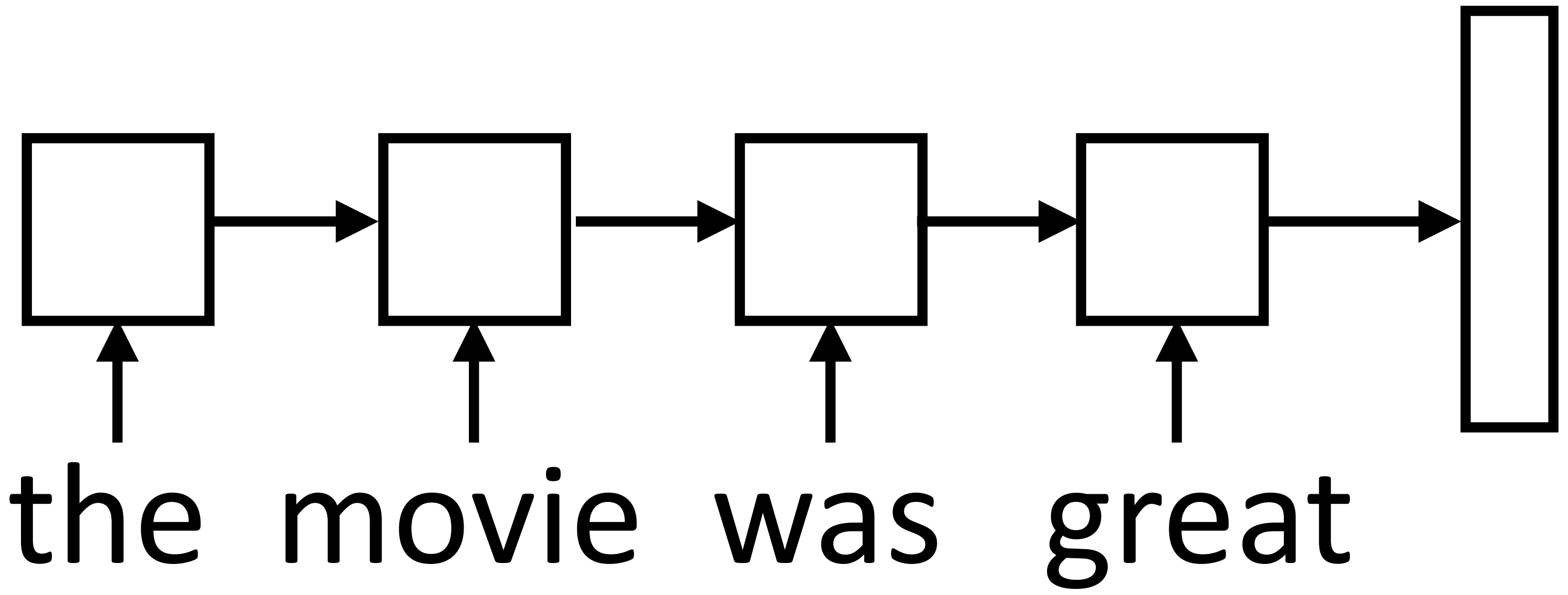
In the words of Ray Mooney...

"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

Model

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



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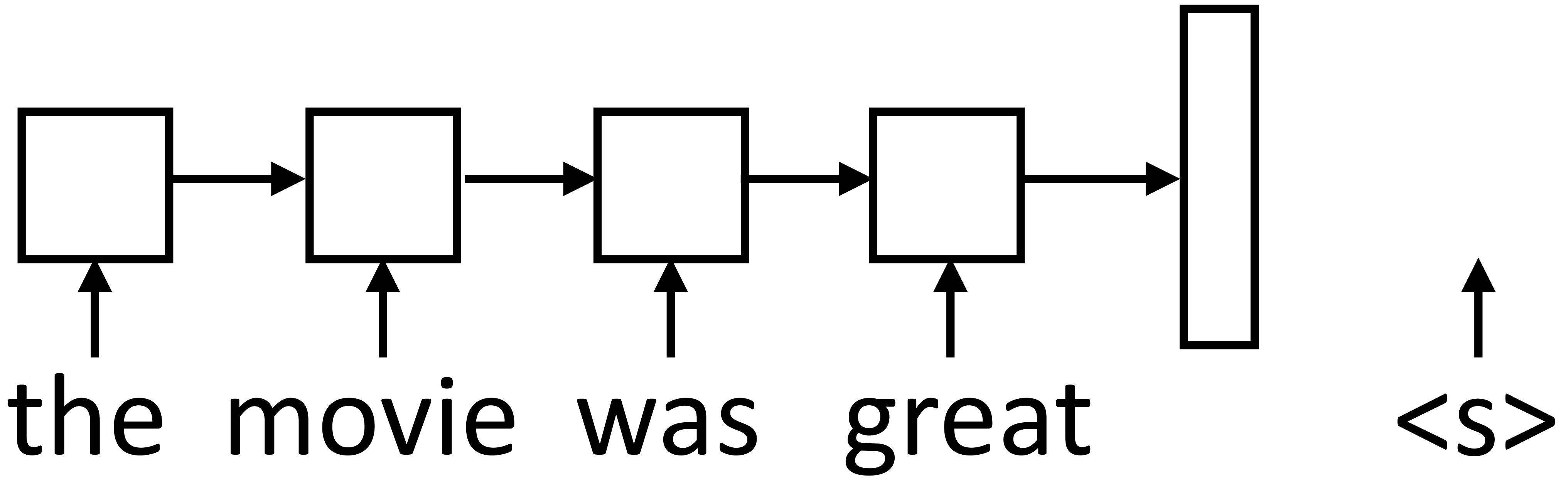

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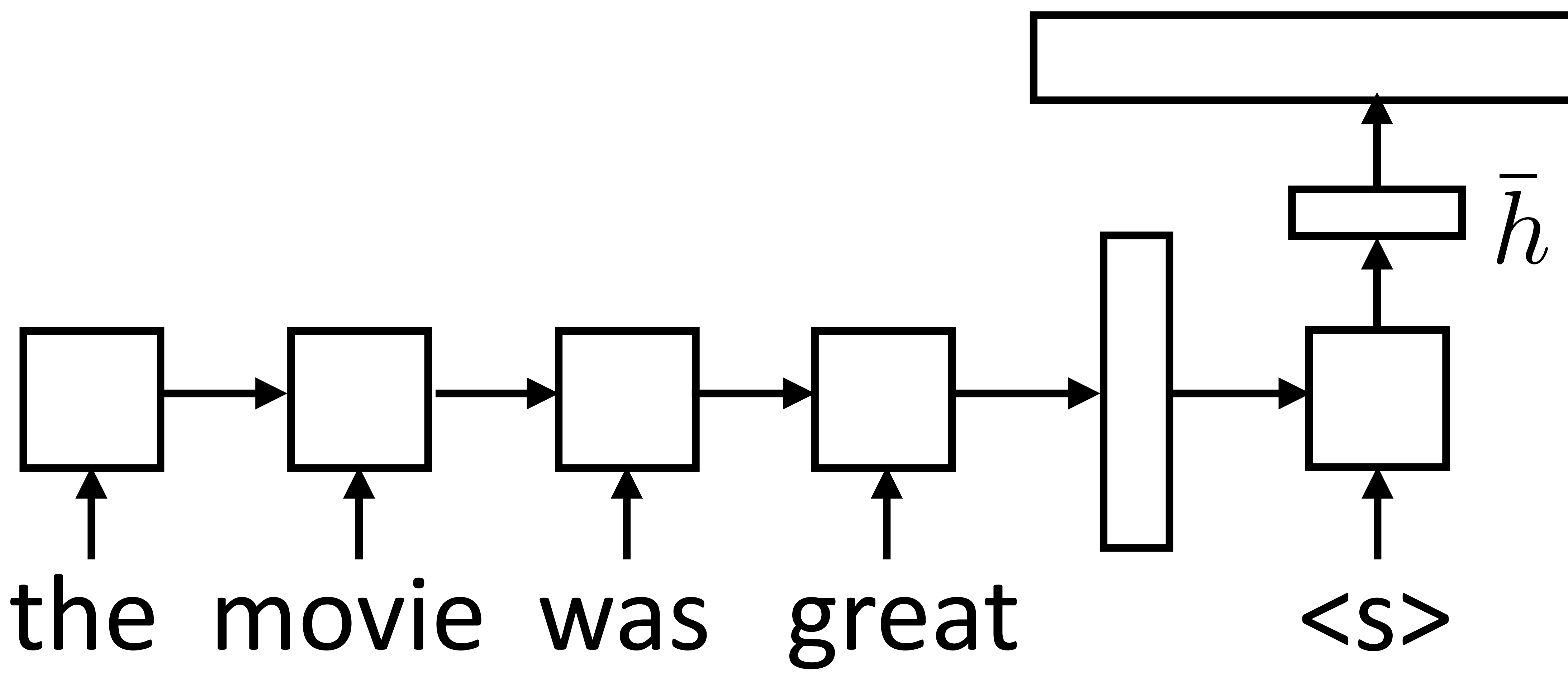
- W size is |vocab| x |hidden state|, softmax over entire vocabulary

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



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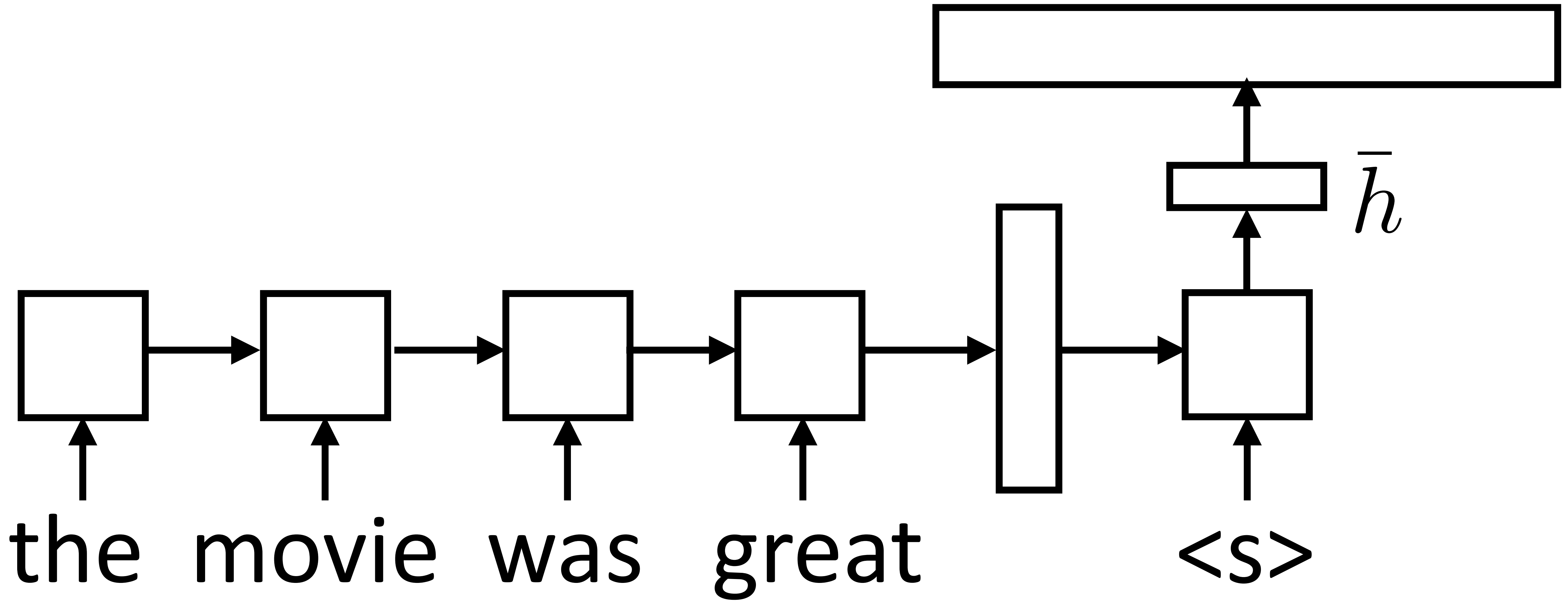

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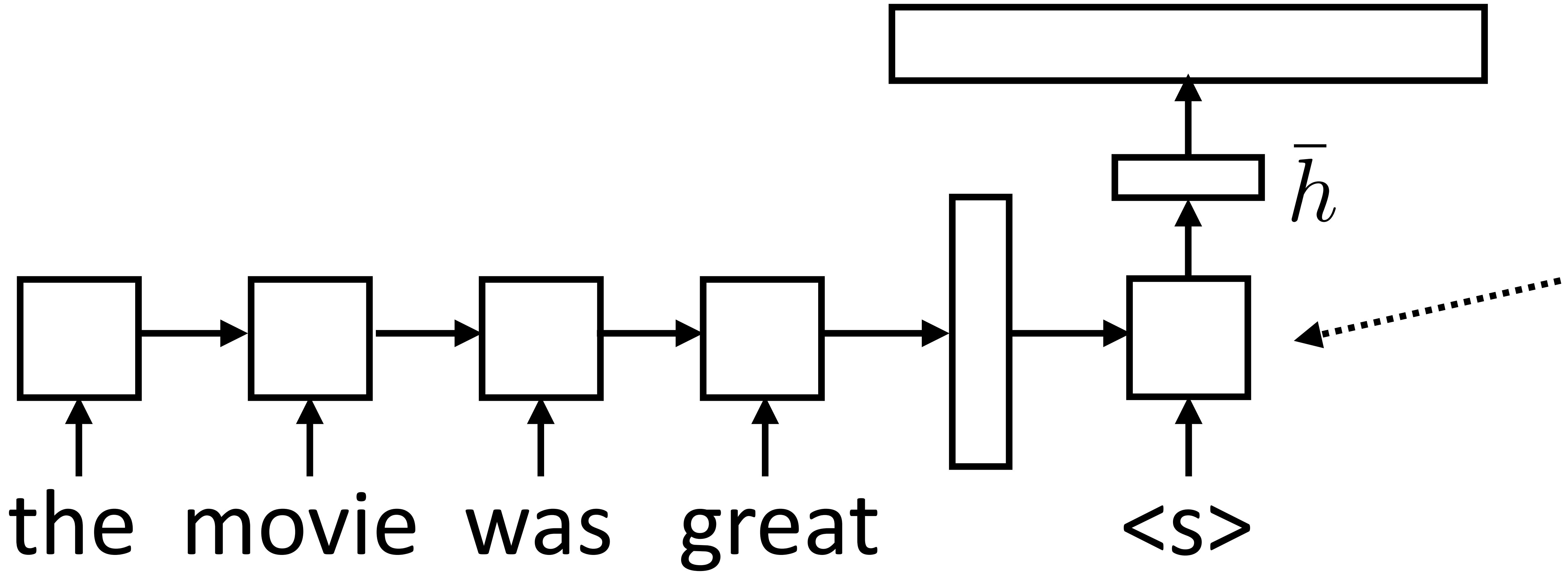

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Decoder has separate parameters from encoder, so this can learn to be a language model (produce a plausible next word given current one)

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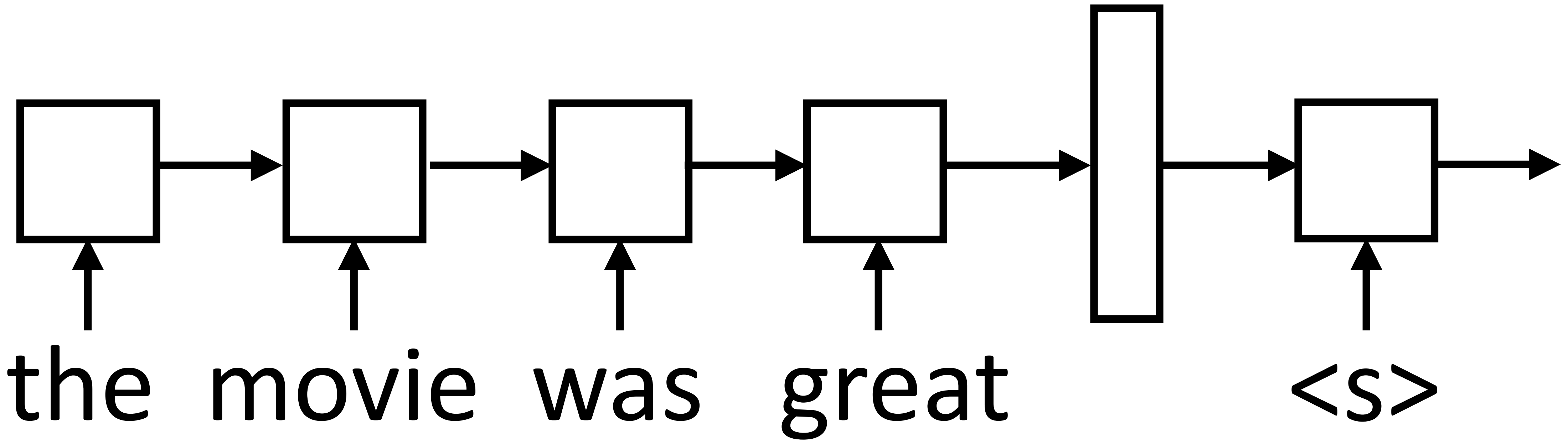

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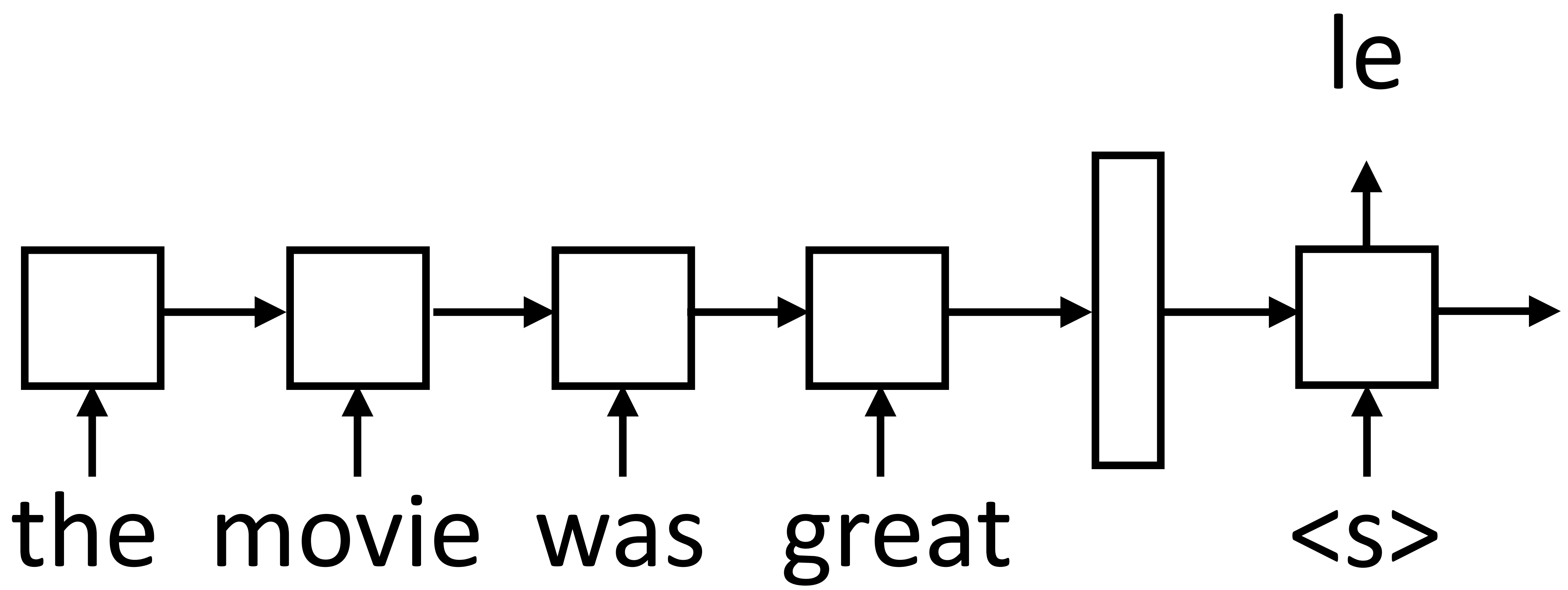

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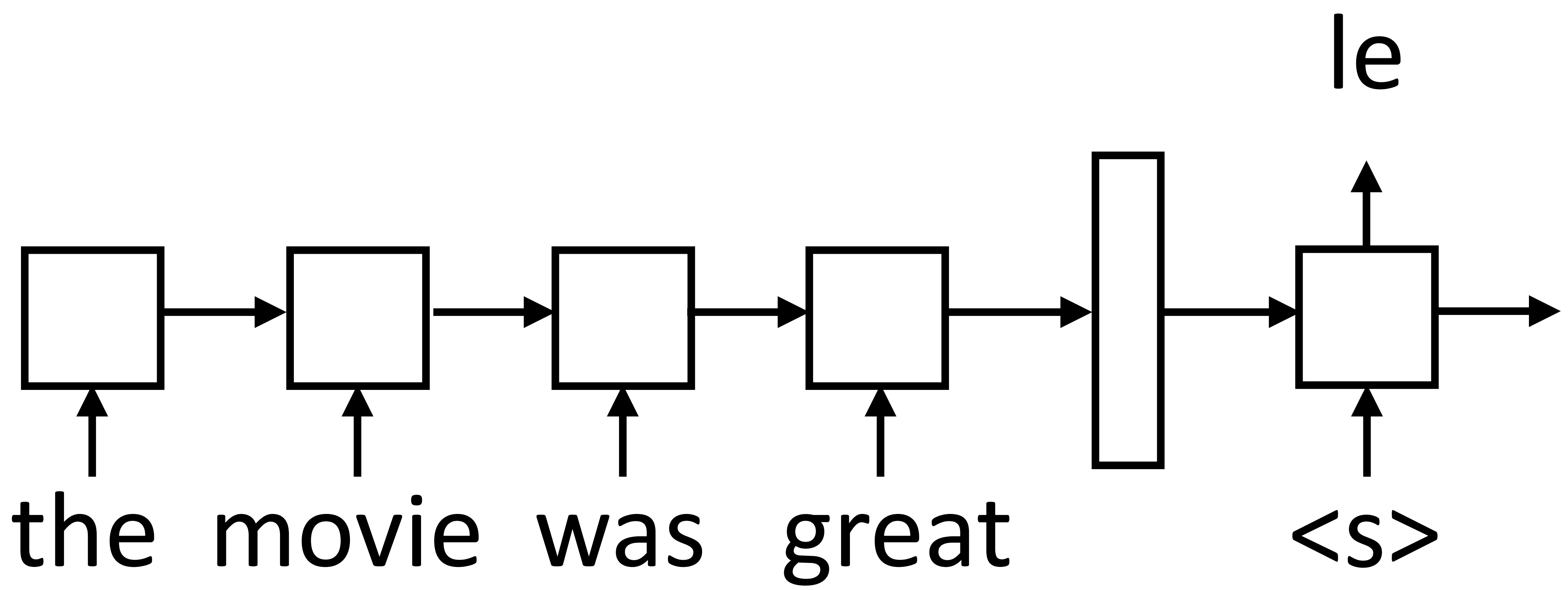

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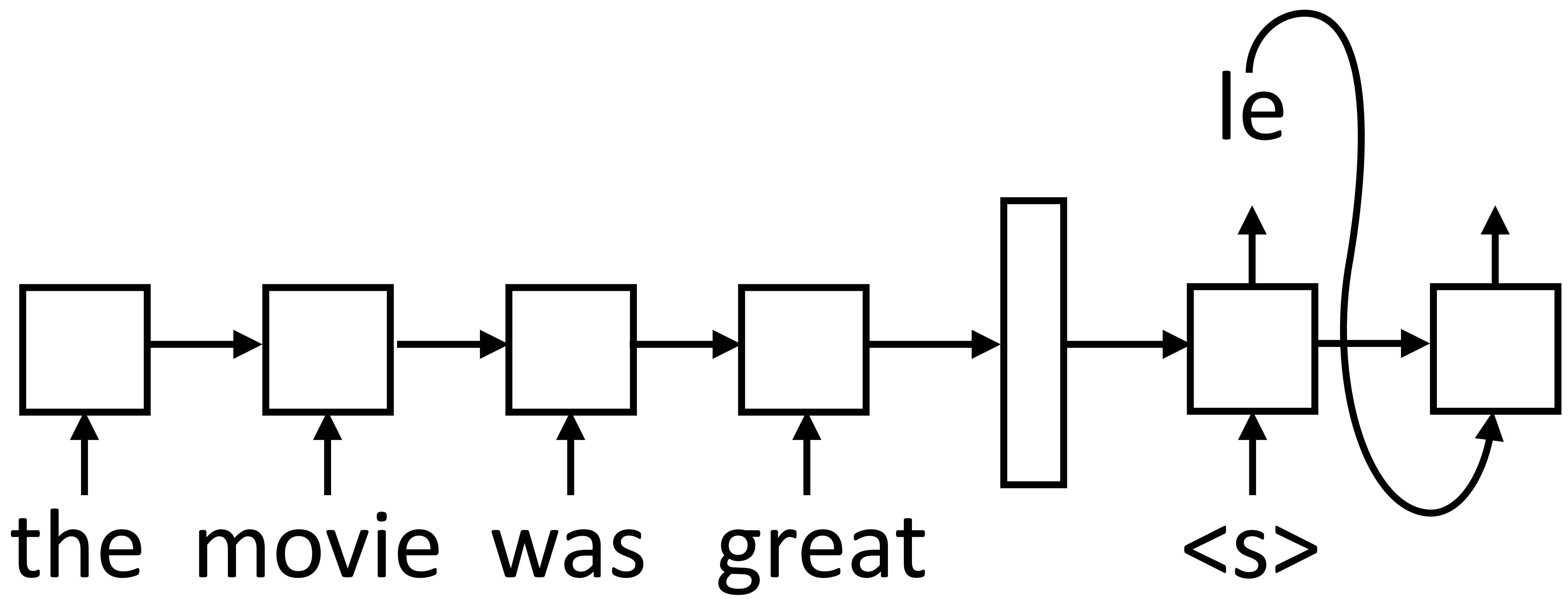

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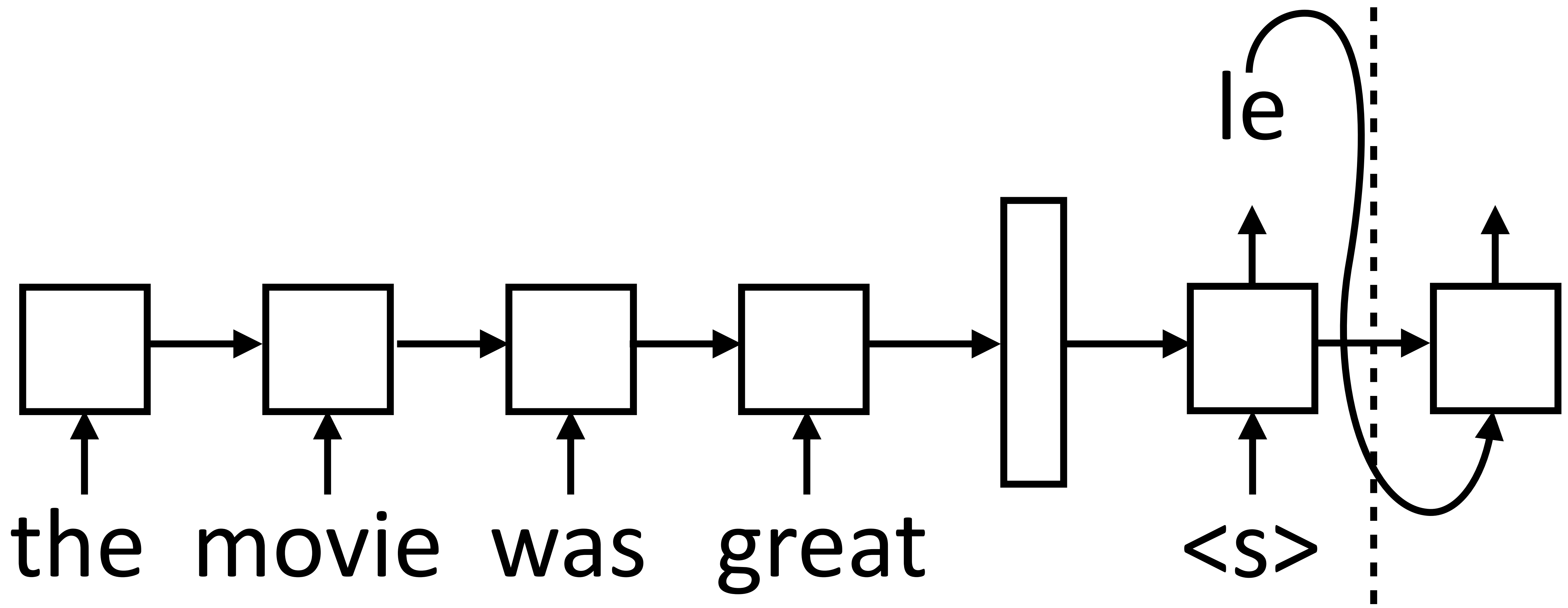

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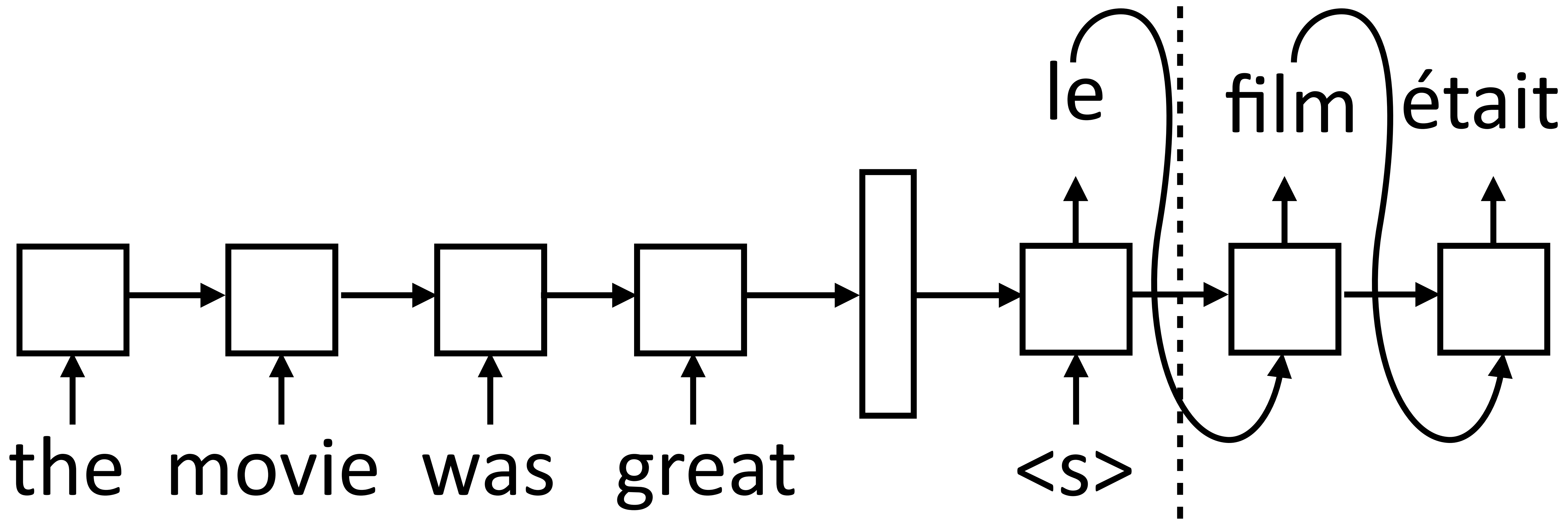

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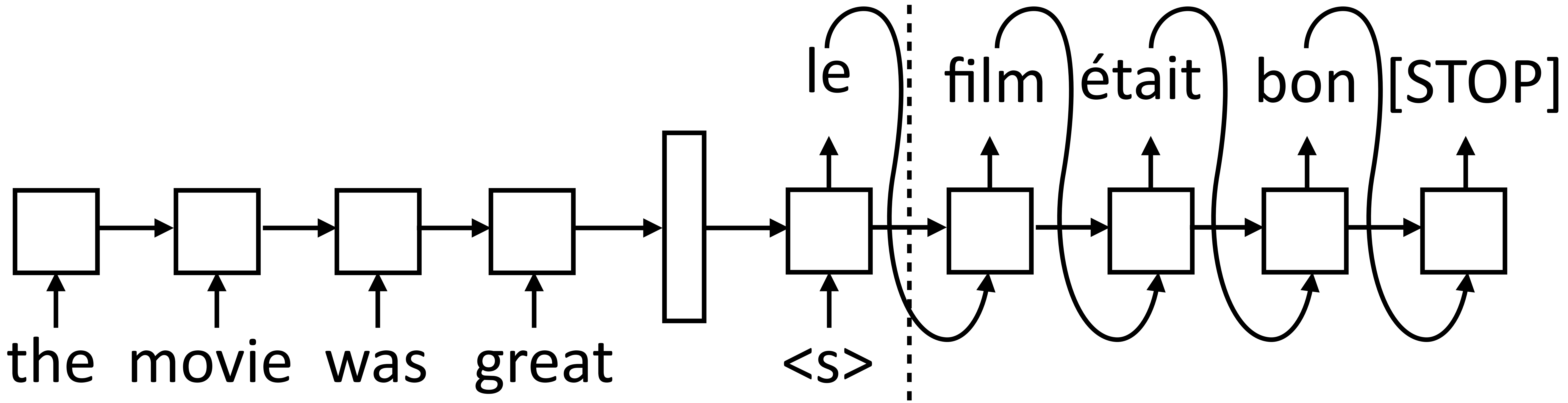

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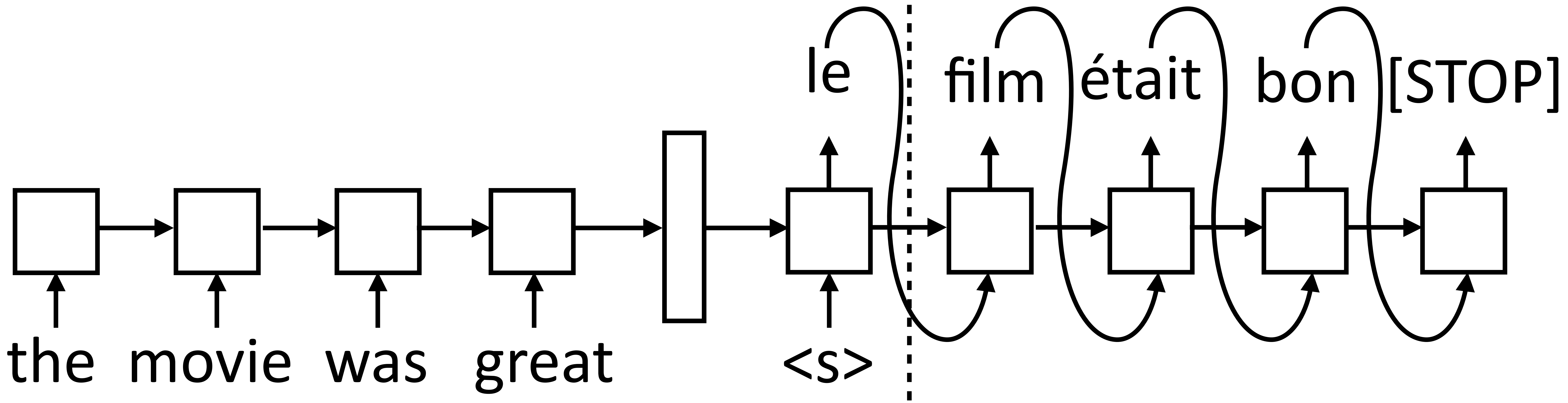

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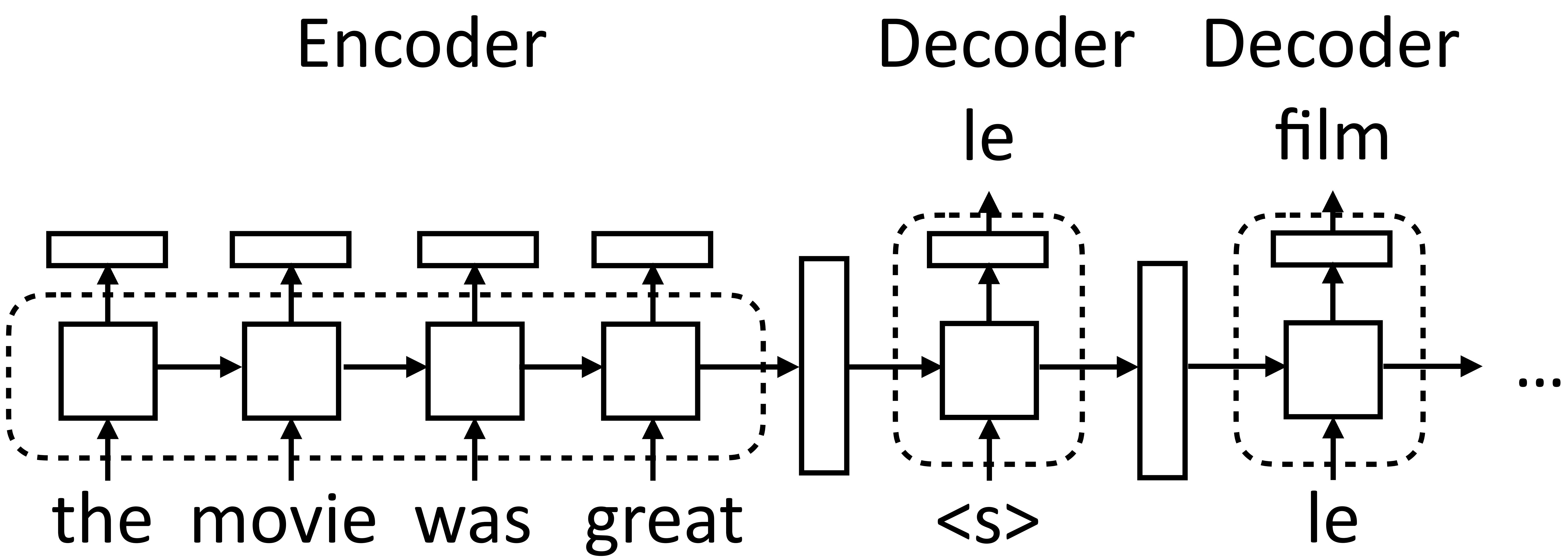
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models



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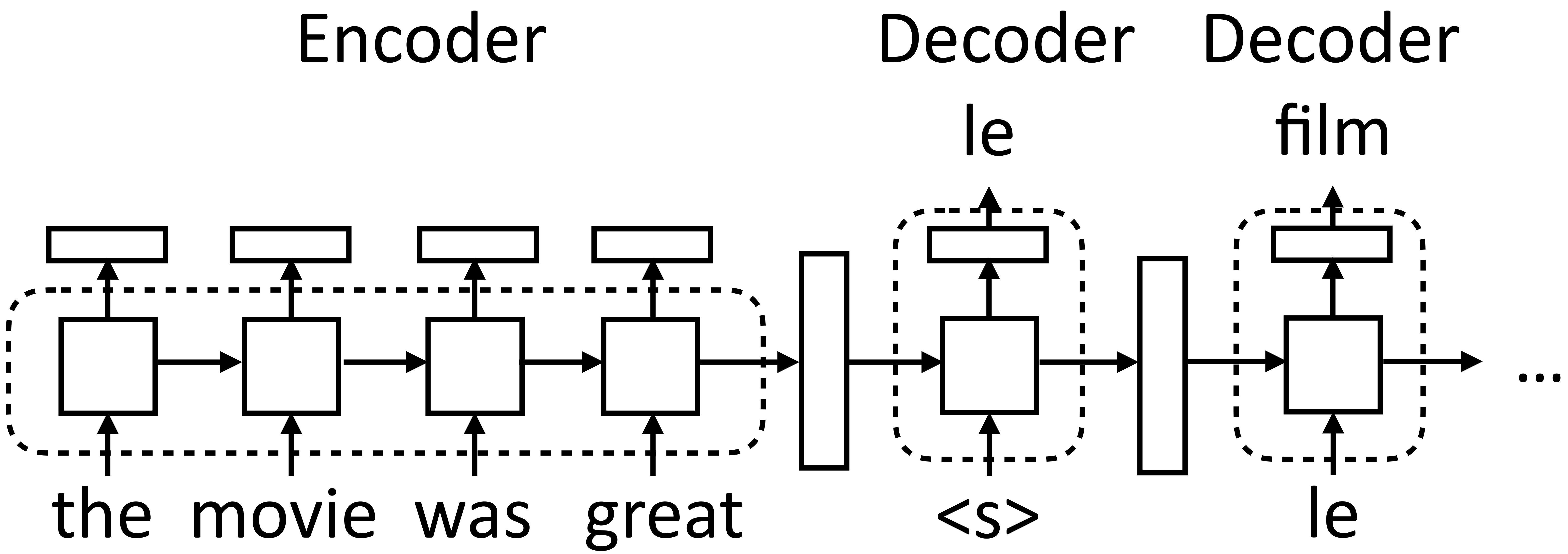

- Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks

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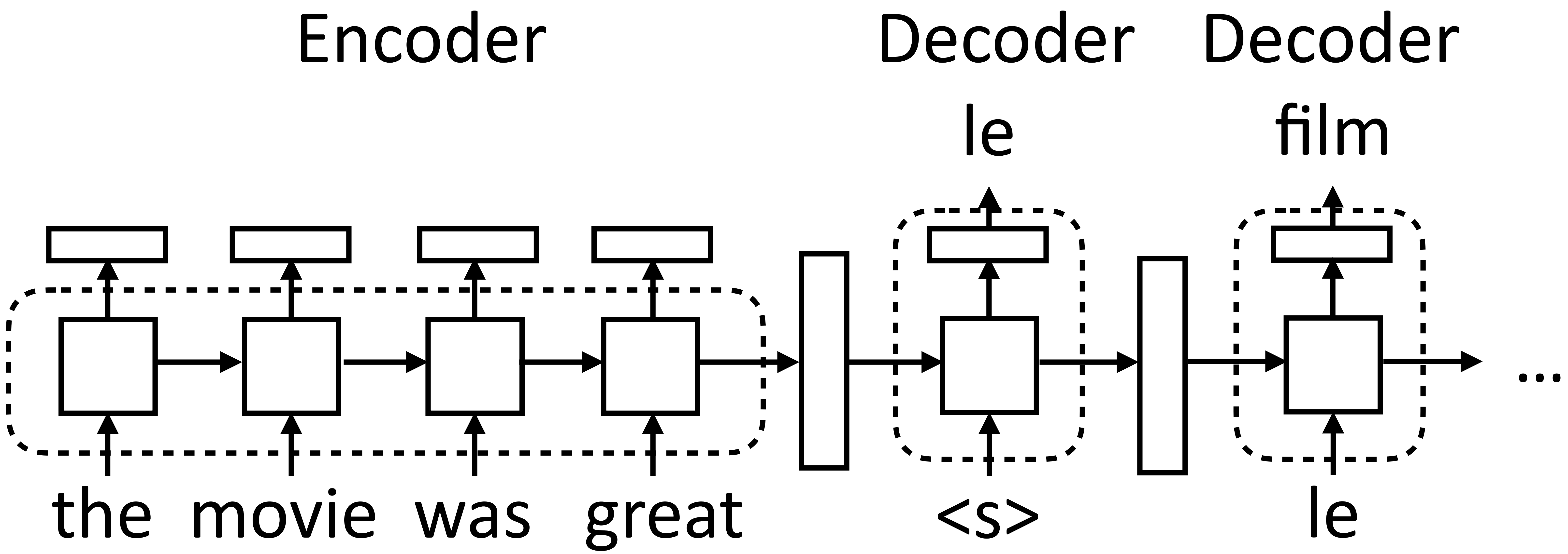
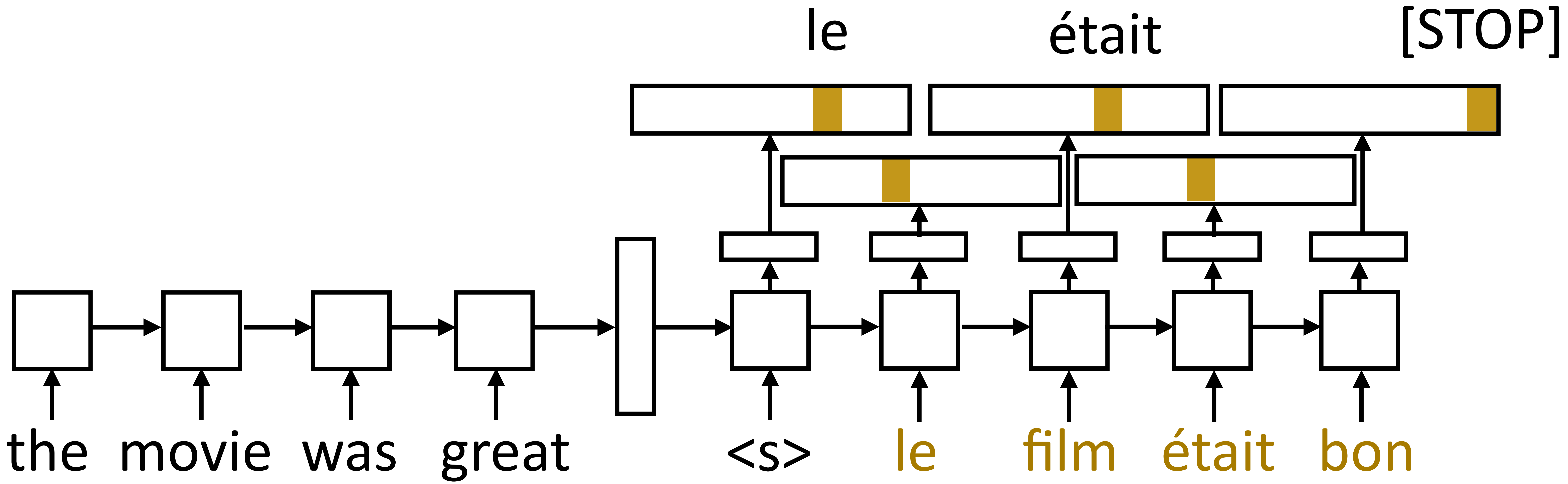


- Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks
- Decoder: separate module, single cell. Takes two inputs: hidden state (vector *h* or tuple (*h*, *c*)) and previous token. Outputs token + new state

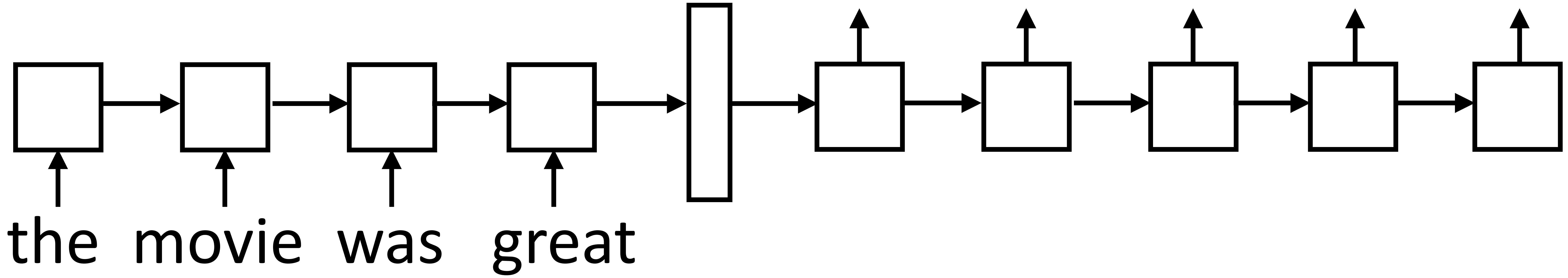
Training



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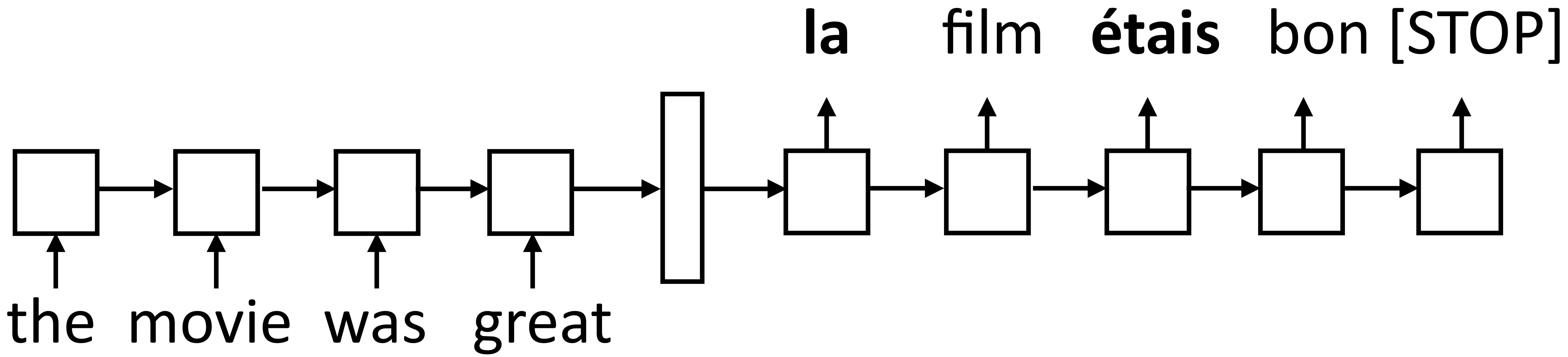

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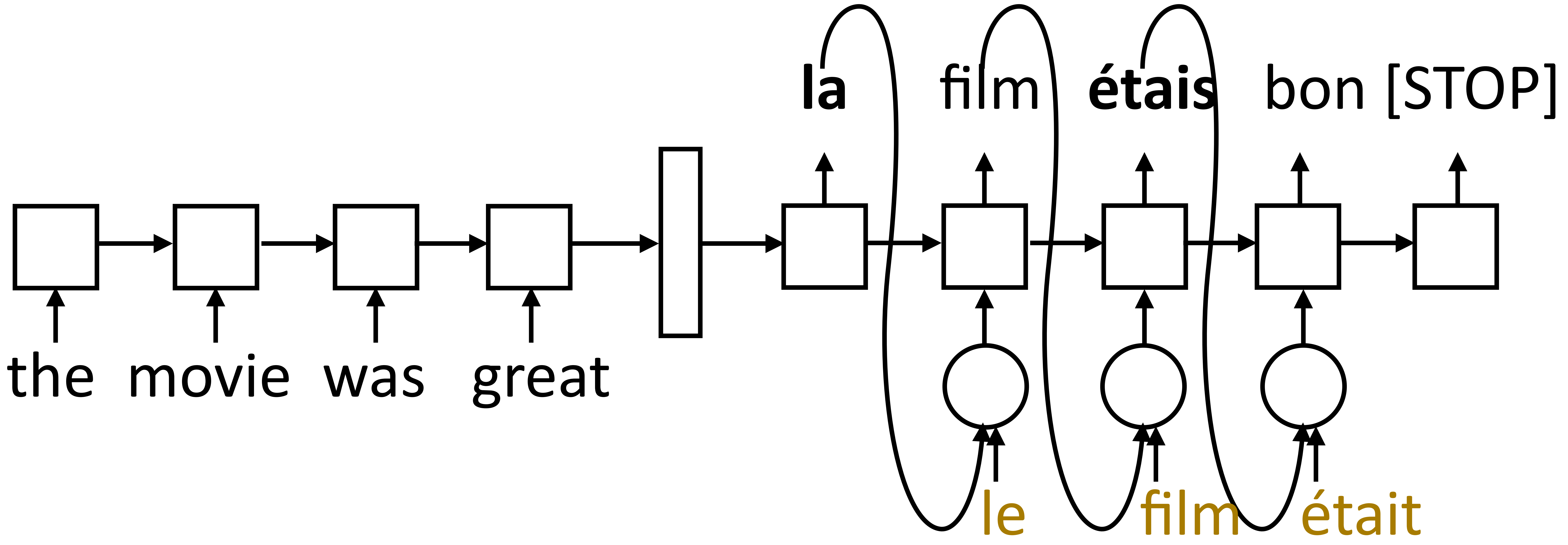

- Scheduled sampling: with probability *p*, take the gold as input, else take the model's prediction

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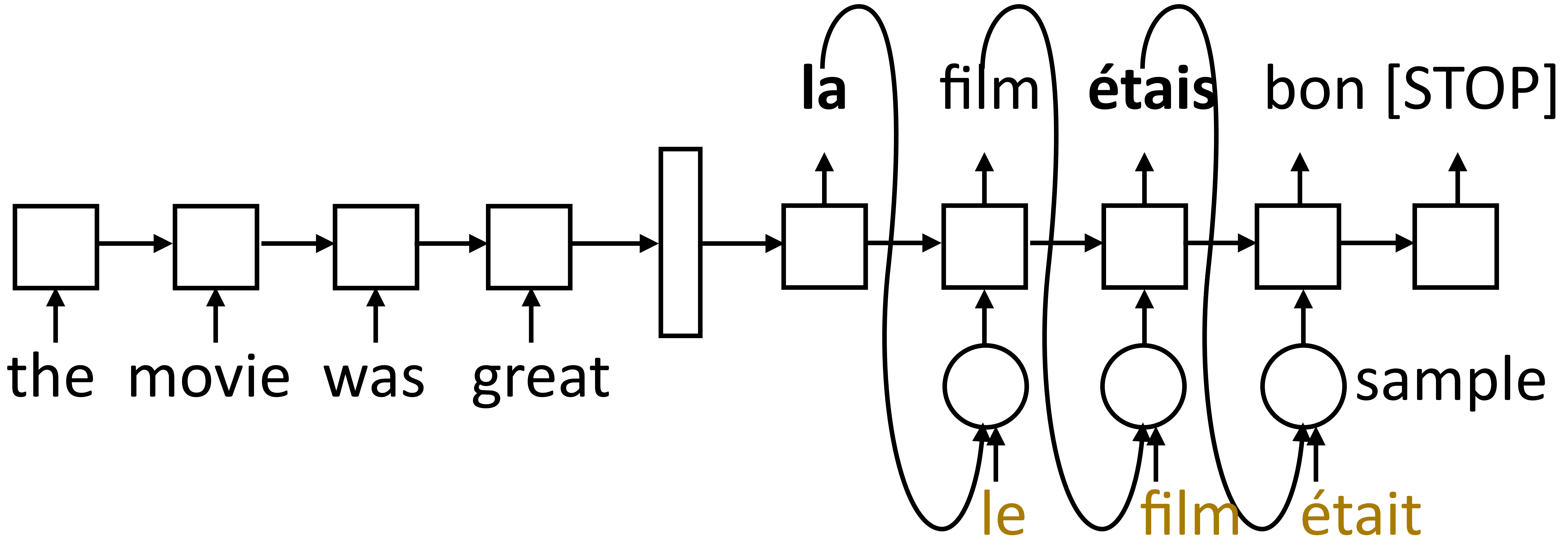

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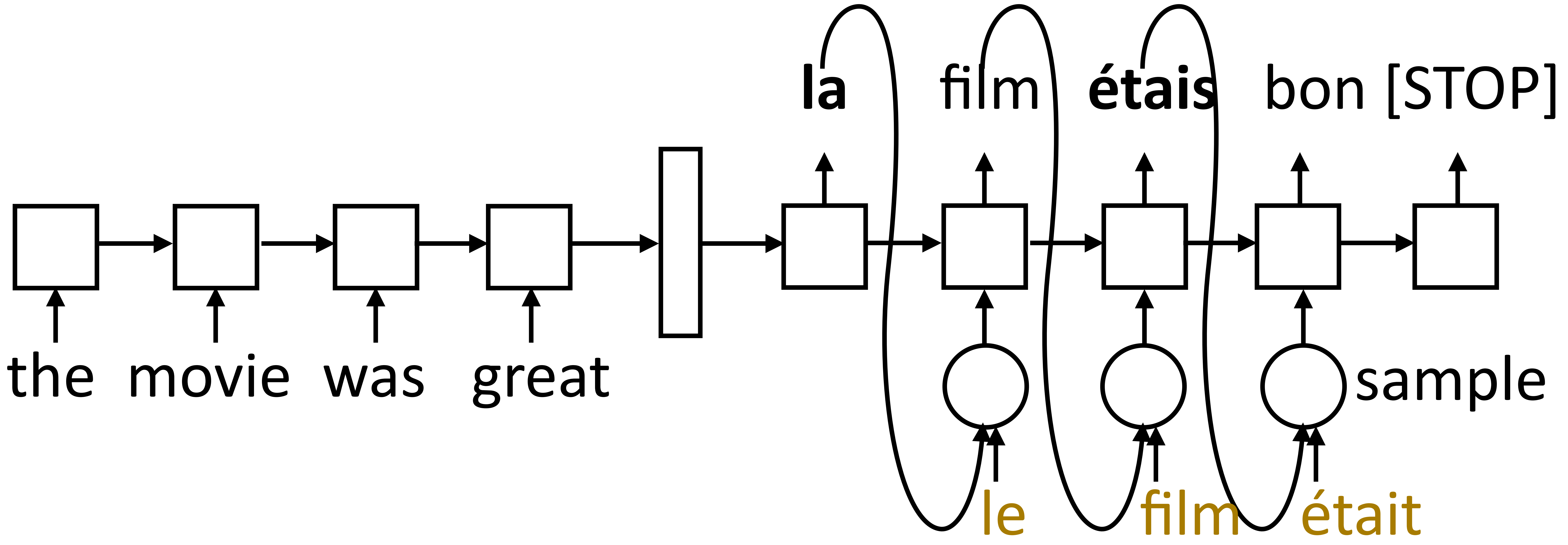

- Scheduled sampling: with probability p, take the gold as input, else take the model's prediction
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- Ideally (in theory), use RL for this…

Bengio et al. (2015)

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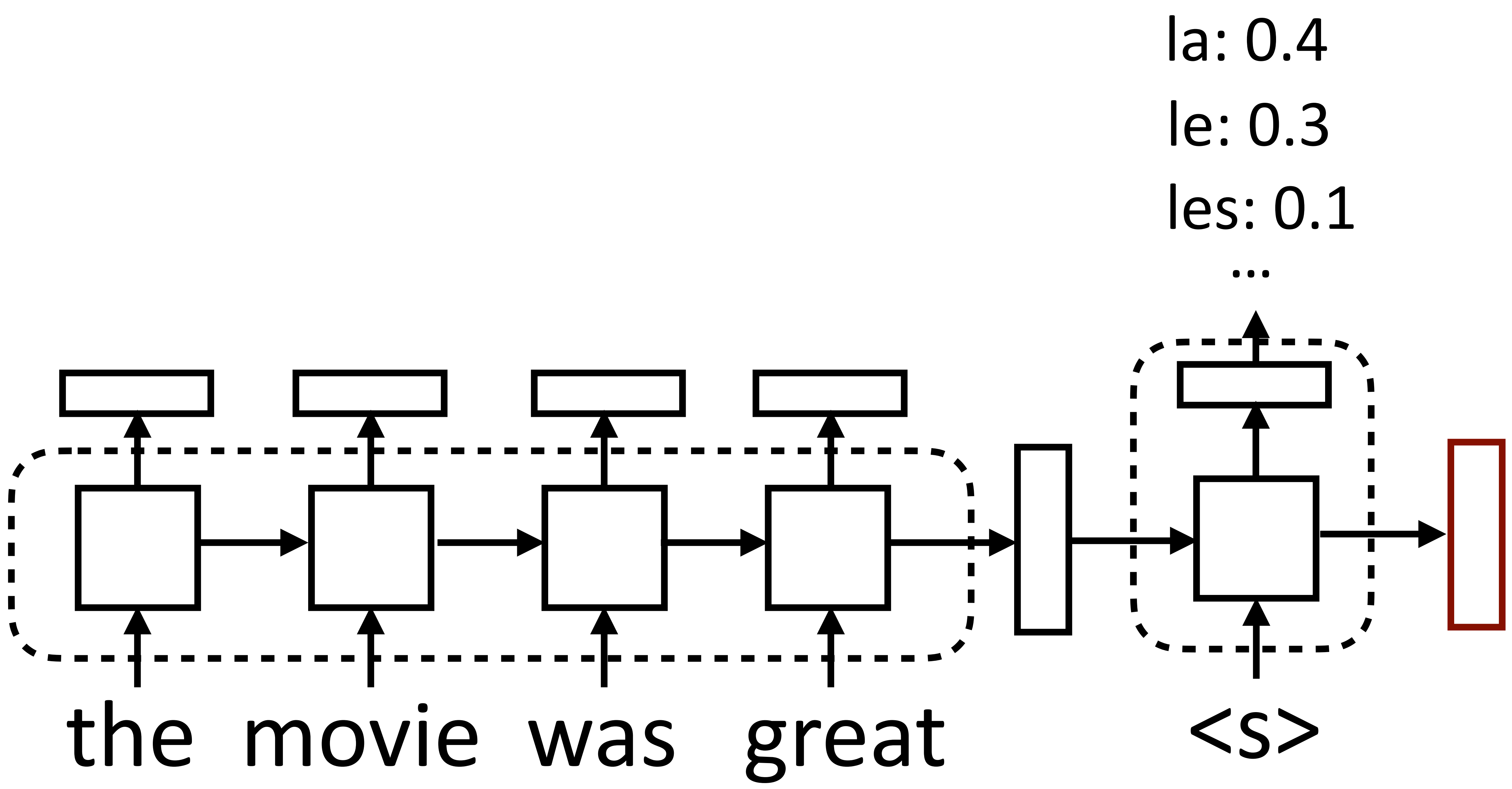
- Encoder: Can be a CNN/LSTM/…
- Decoder: also flexible in terms of architecture (more later). Execute one step of computation at a time, so computation graph is formulated as taking one input + hidden state
- Beam search: can help with lookahead. Finds the (approximate) highest scoring sequence:

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

Beam Search

- Maintain decoder state, token history in beam



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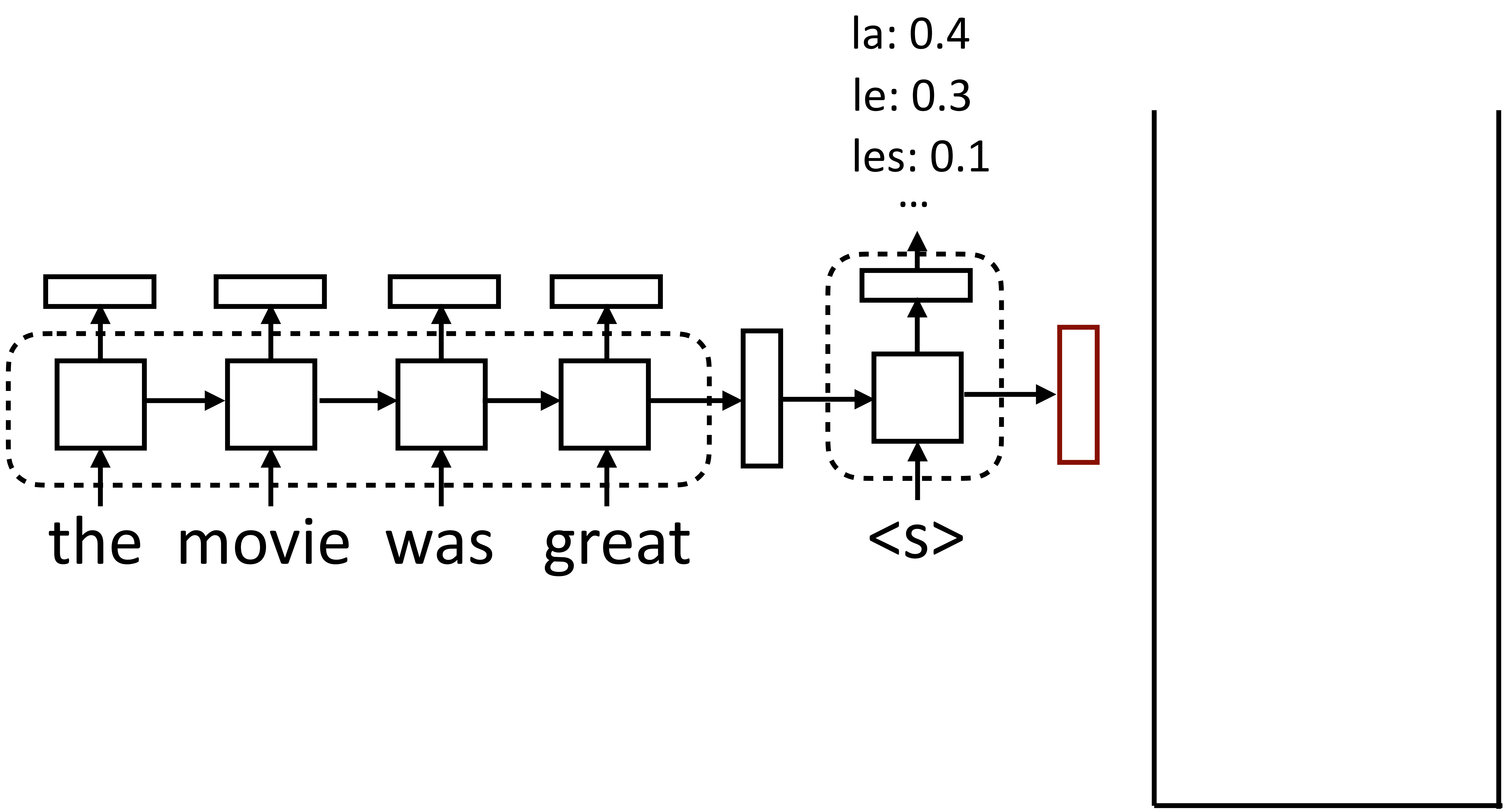

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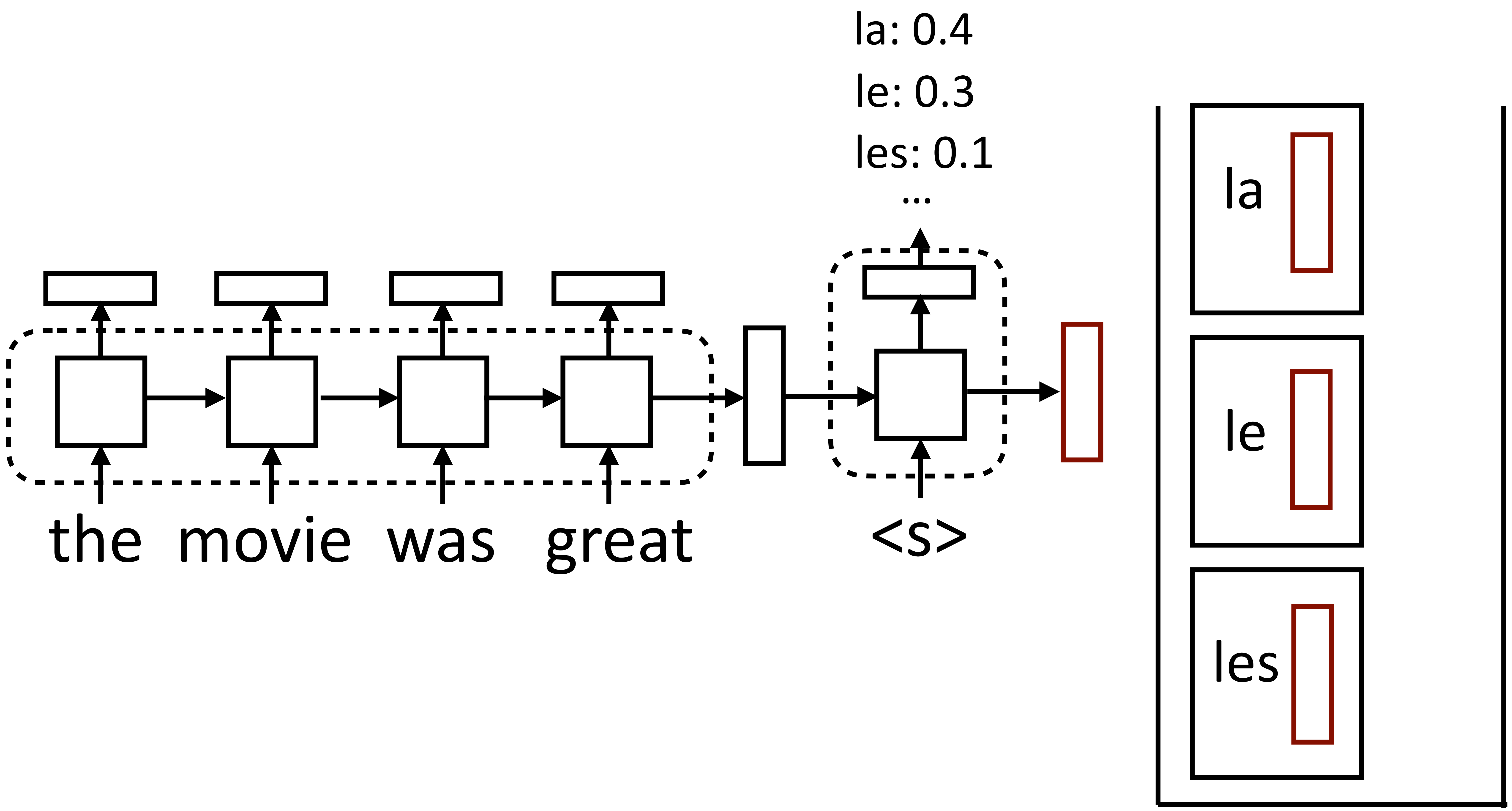

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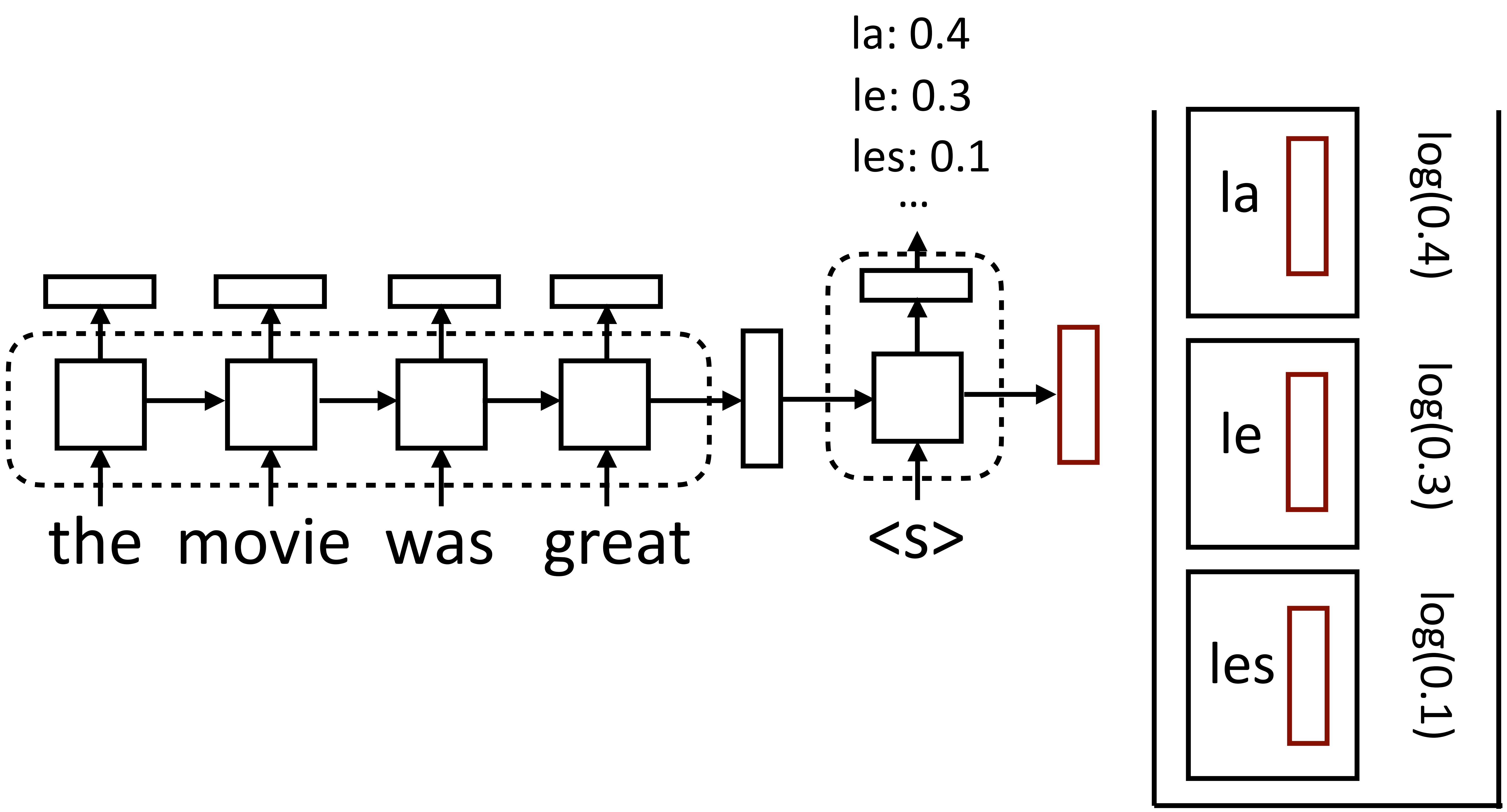

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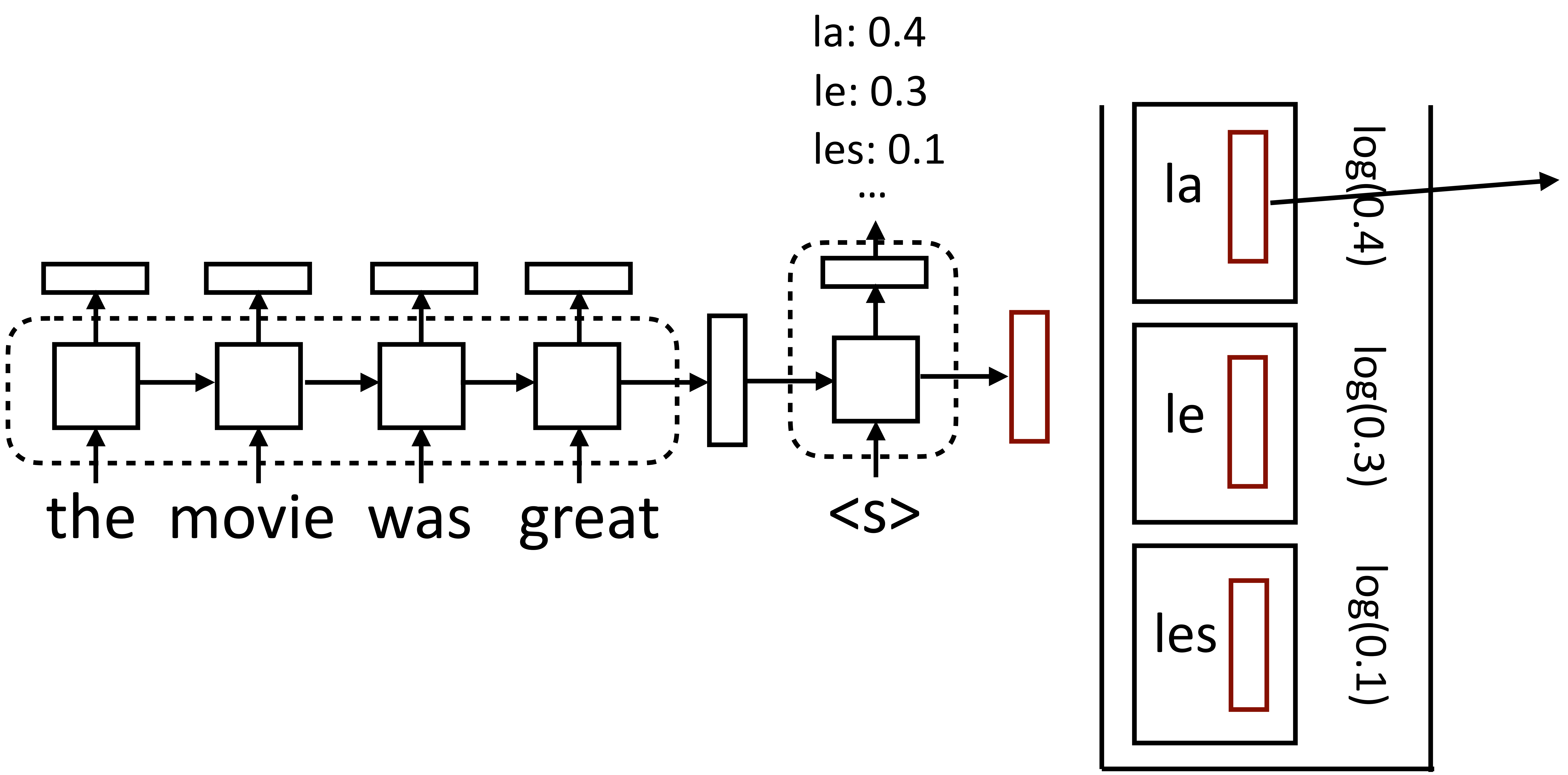

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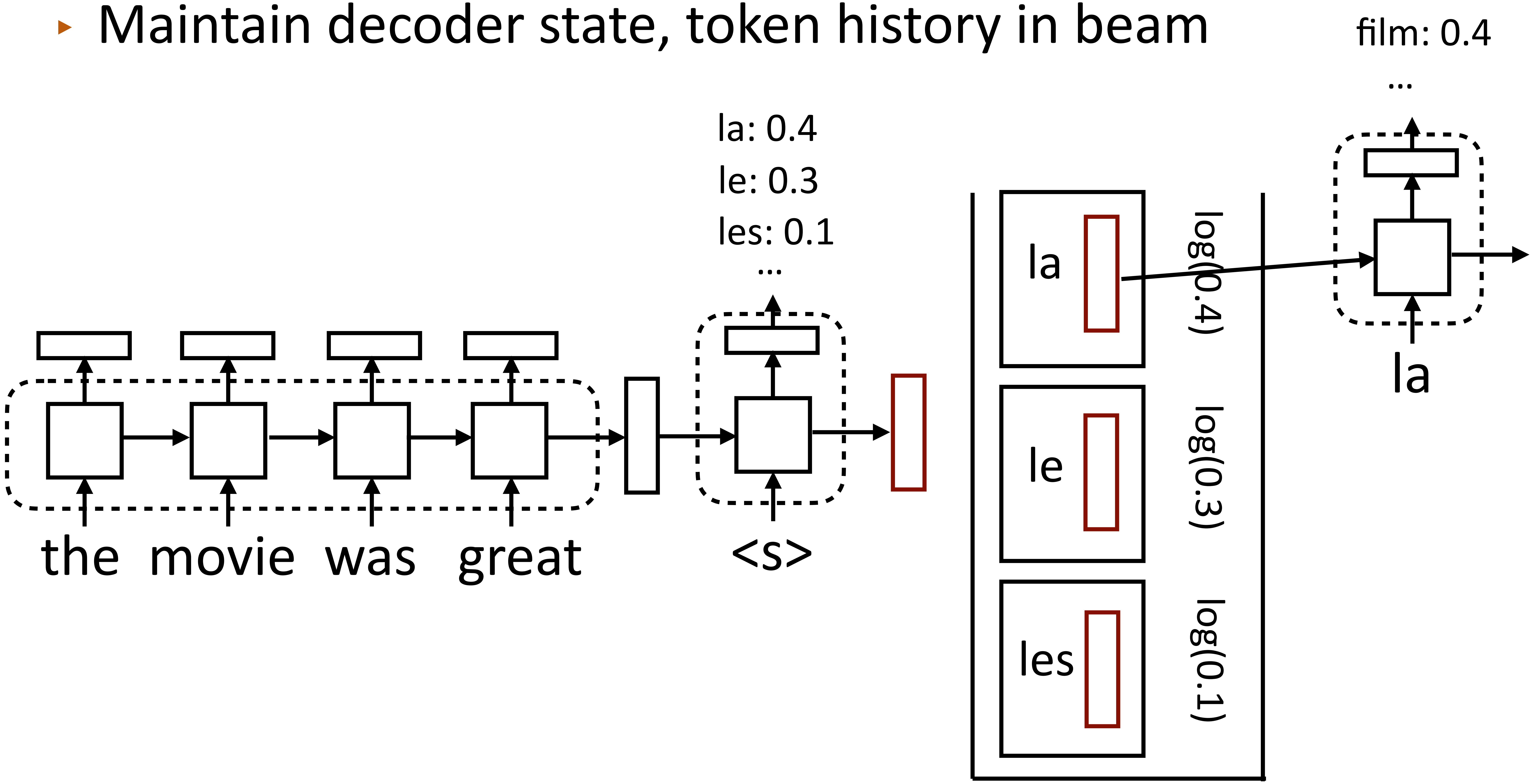

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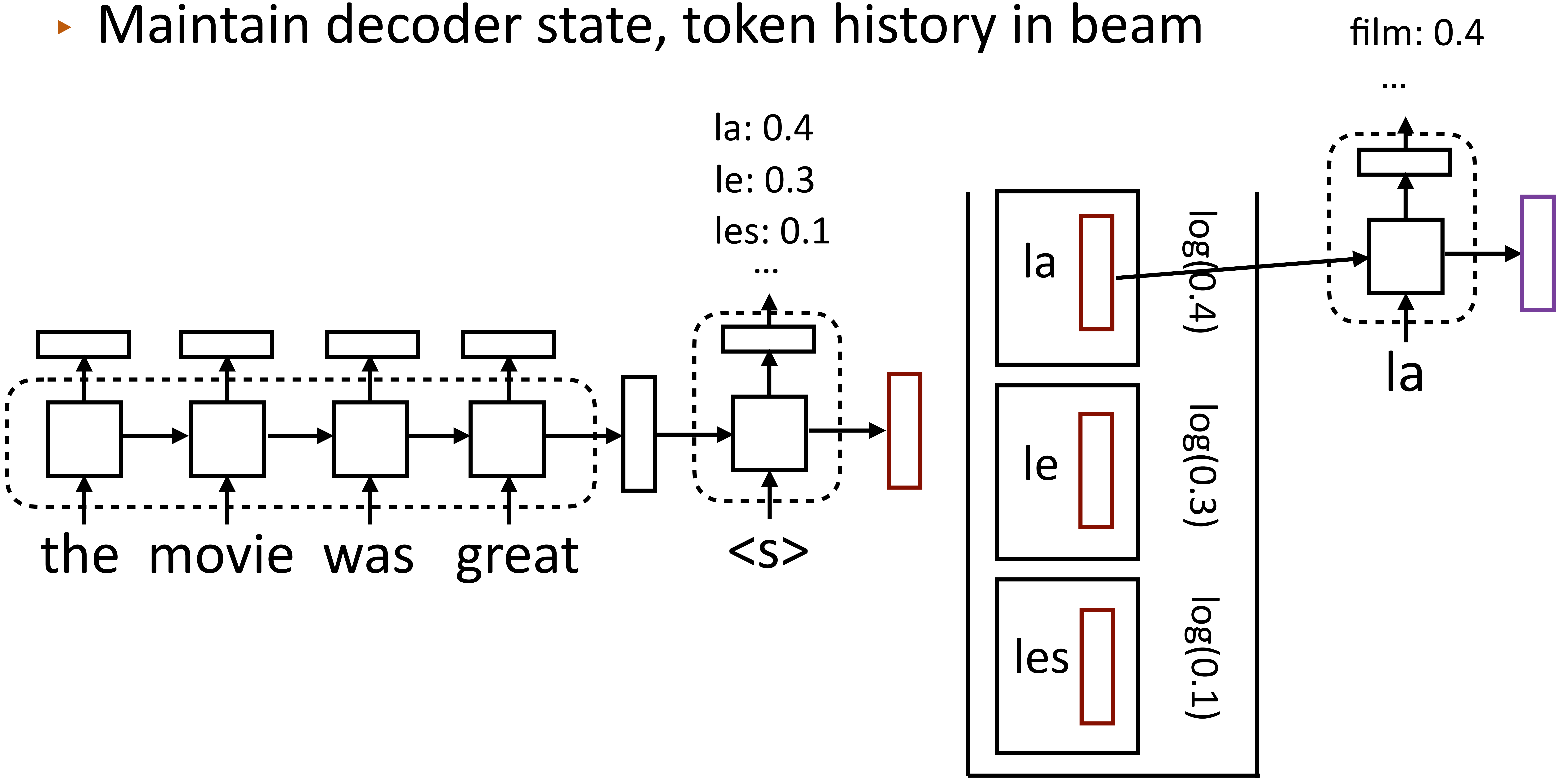

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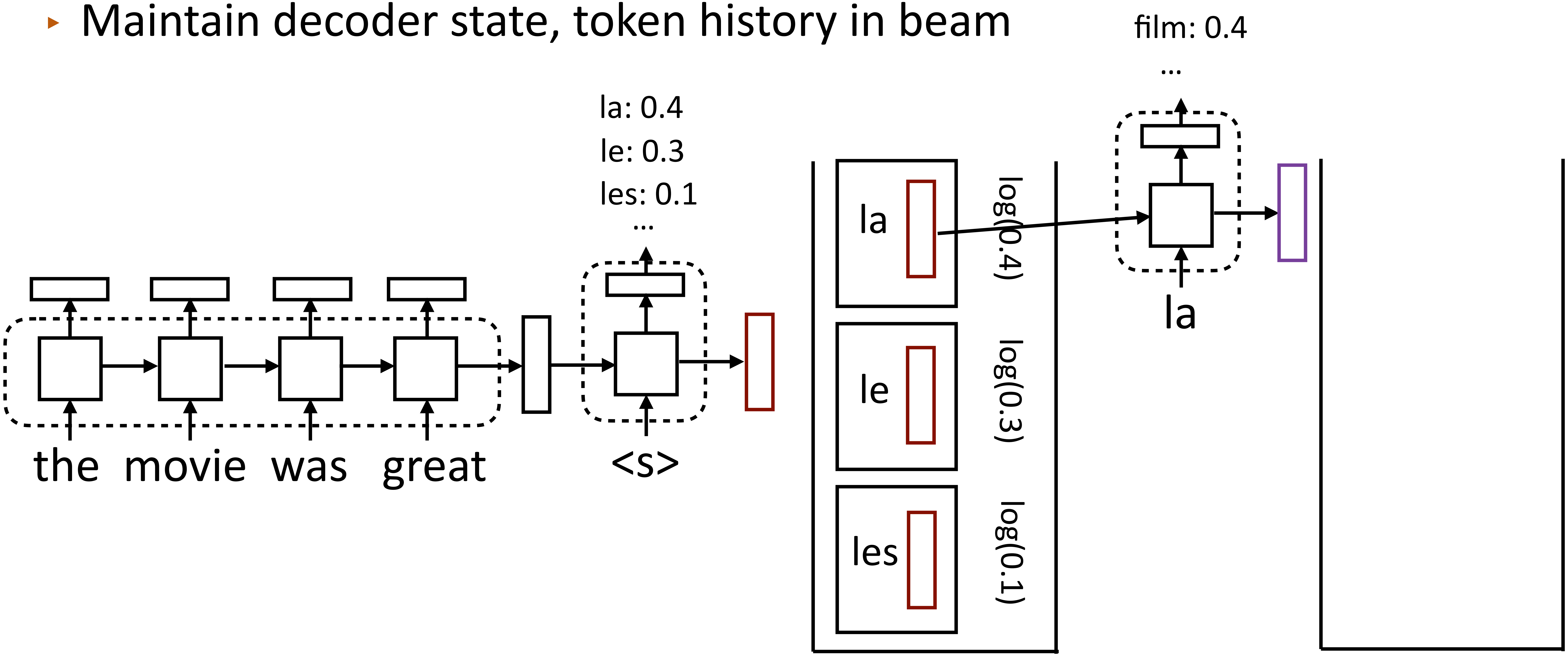

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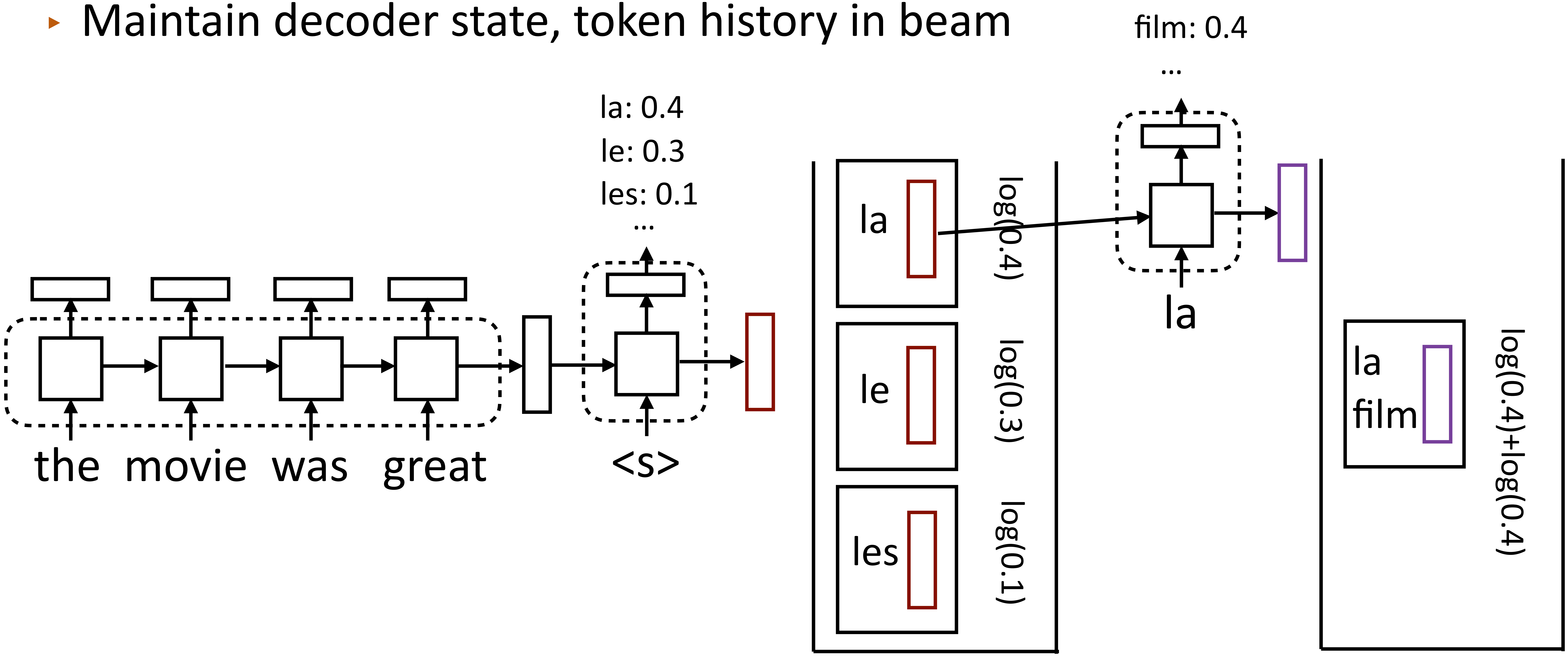

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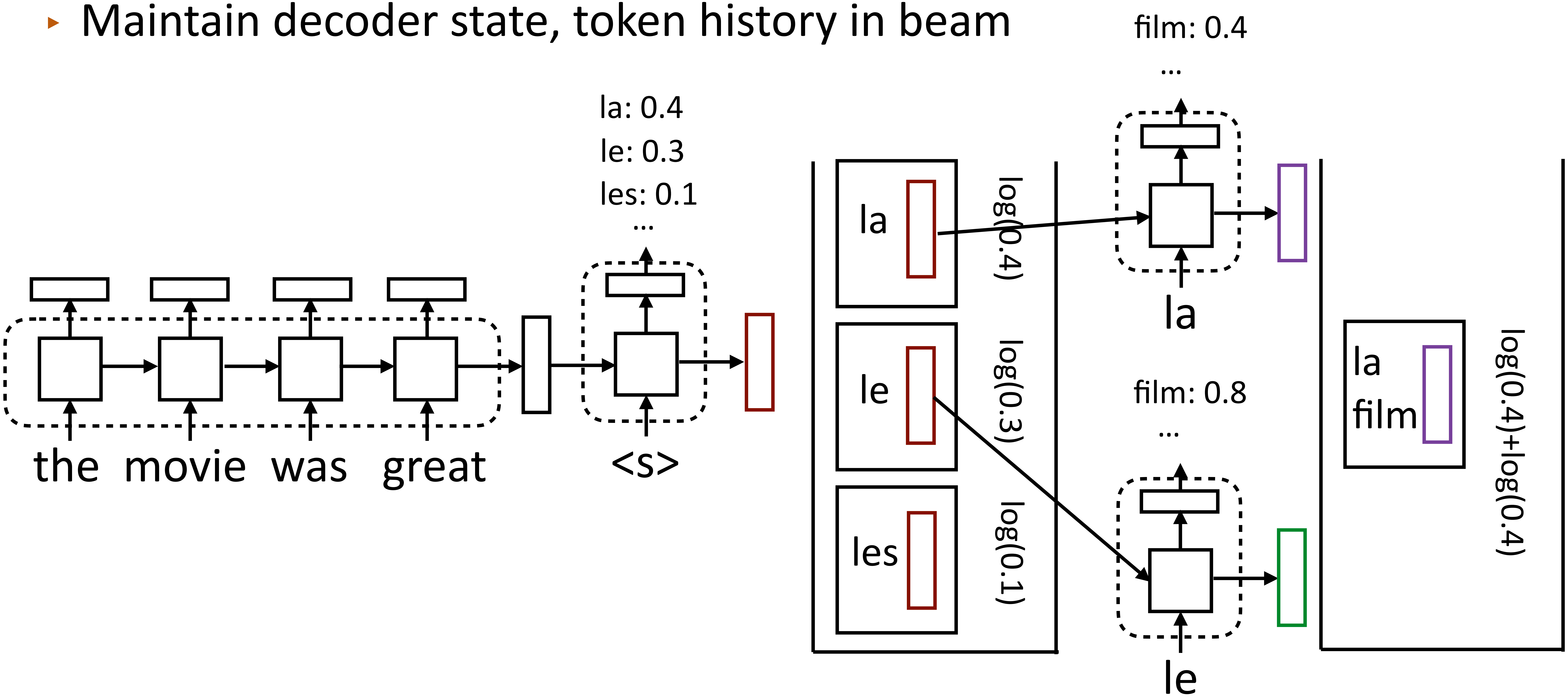

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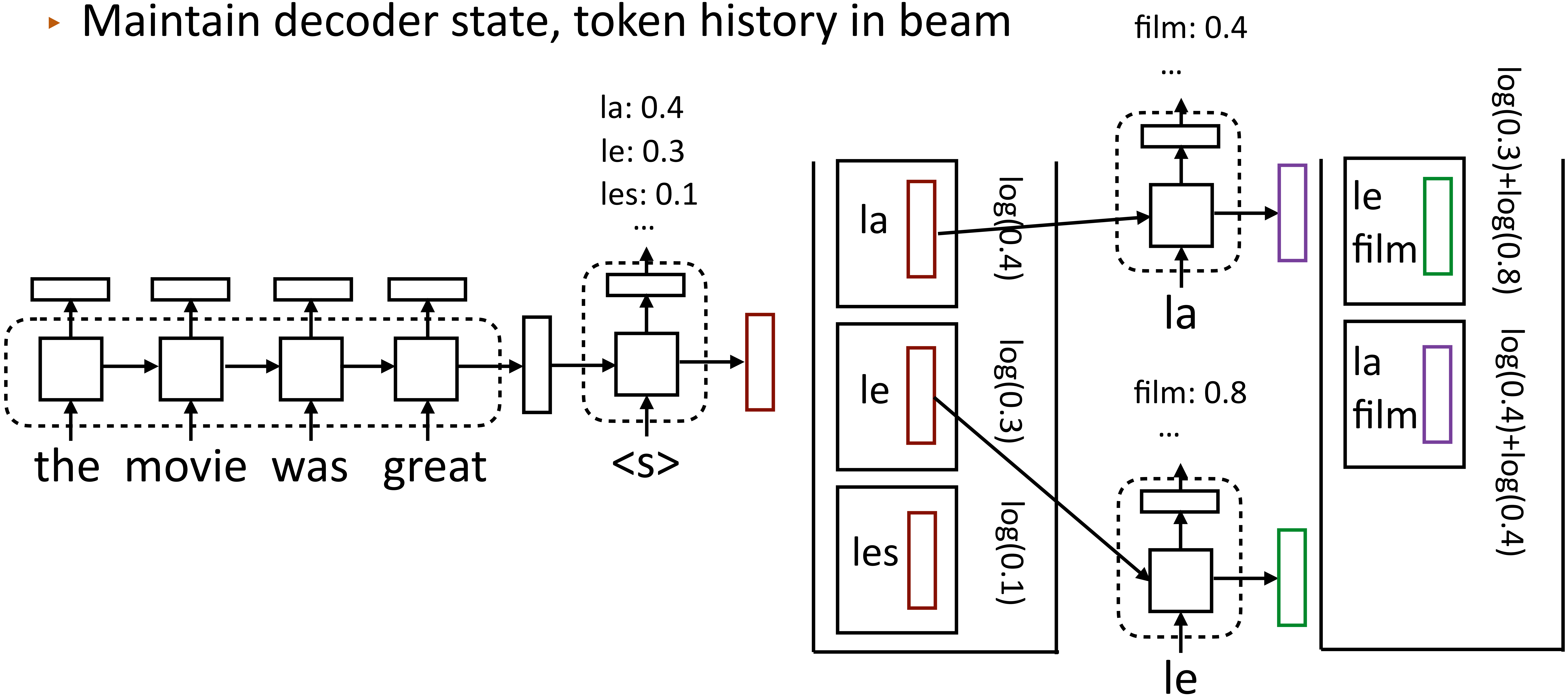

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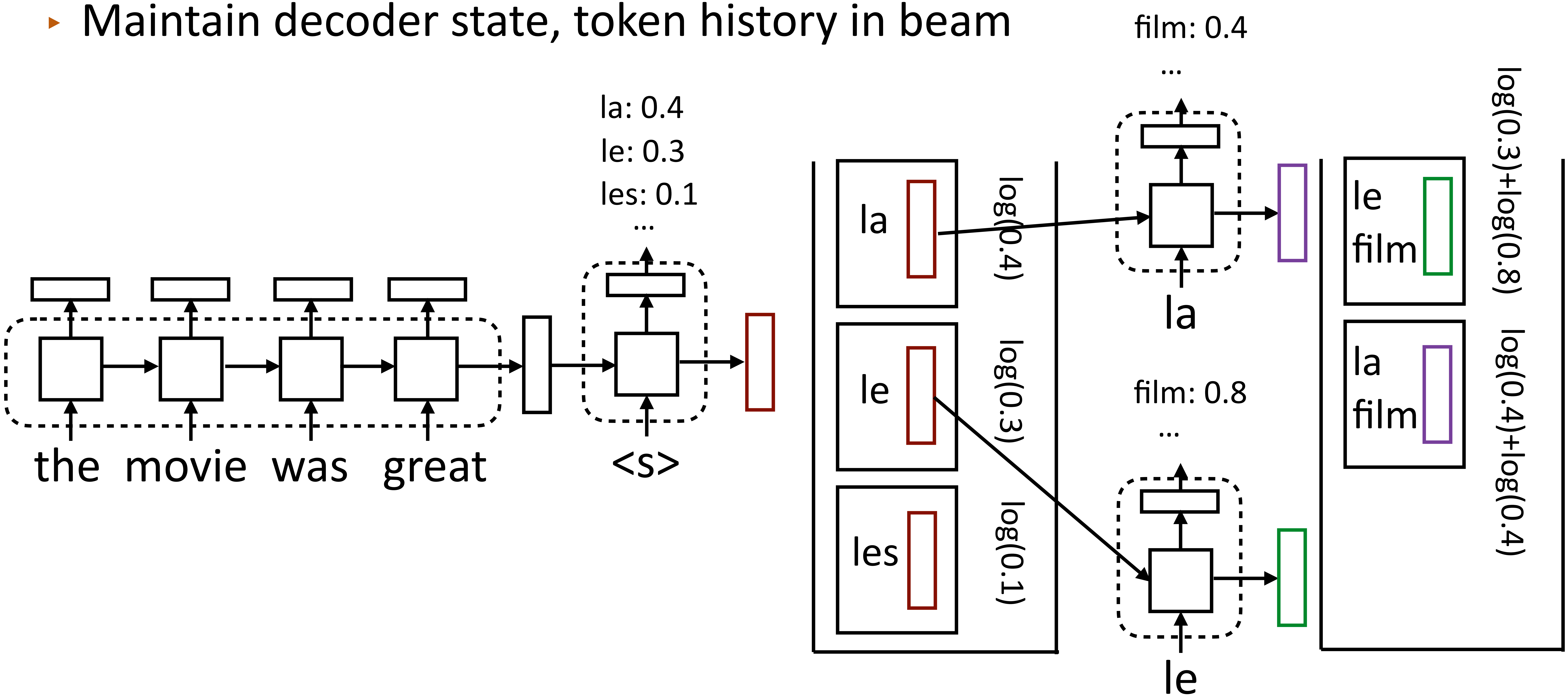

- Do **not** max over the two *film* states! Hidden state vectors are different

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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- No need to have an explicit grammar, simplifies algorithms

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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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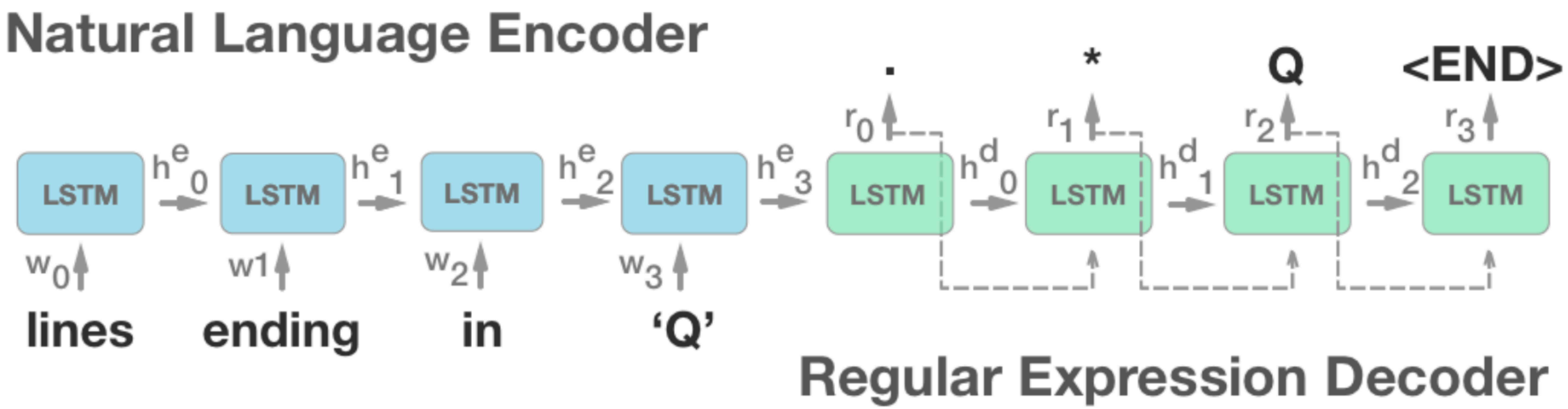

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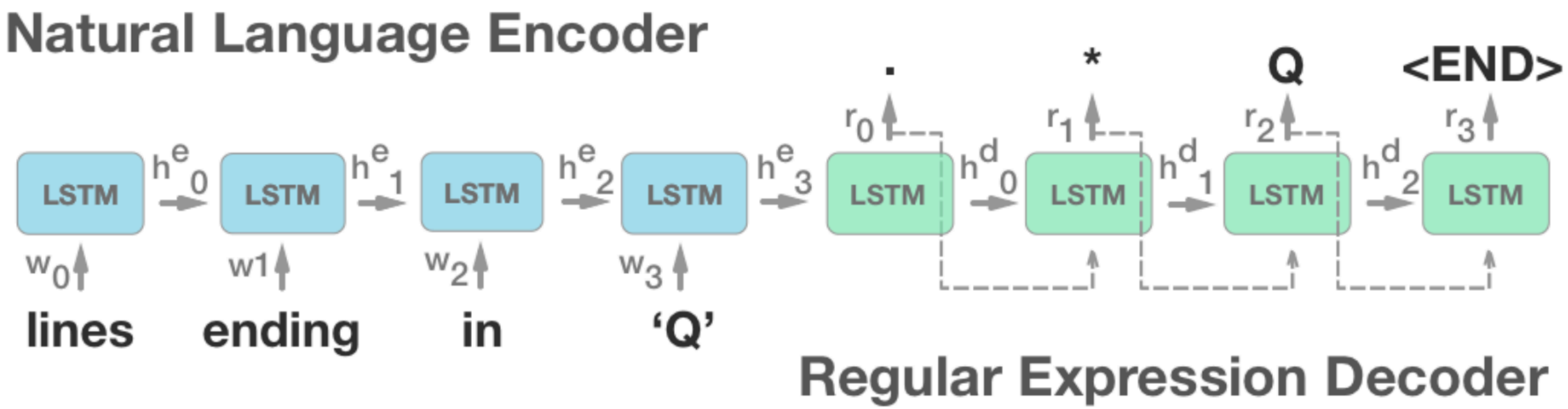

- Problem: requires a lot of data: 10,000 examples needed to get ~60% accuracy on pretty simple regexes

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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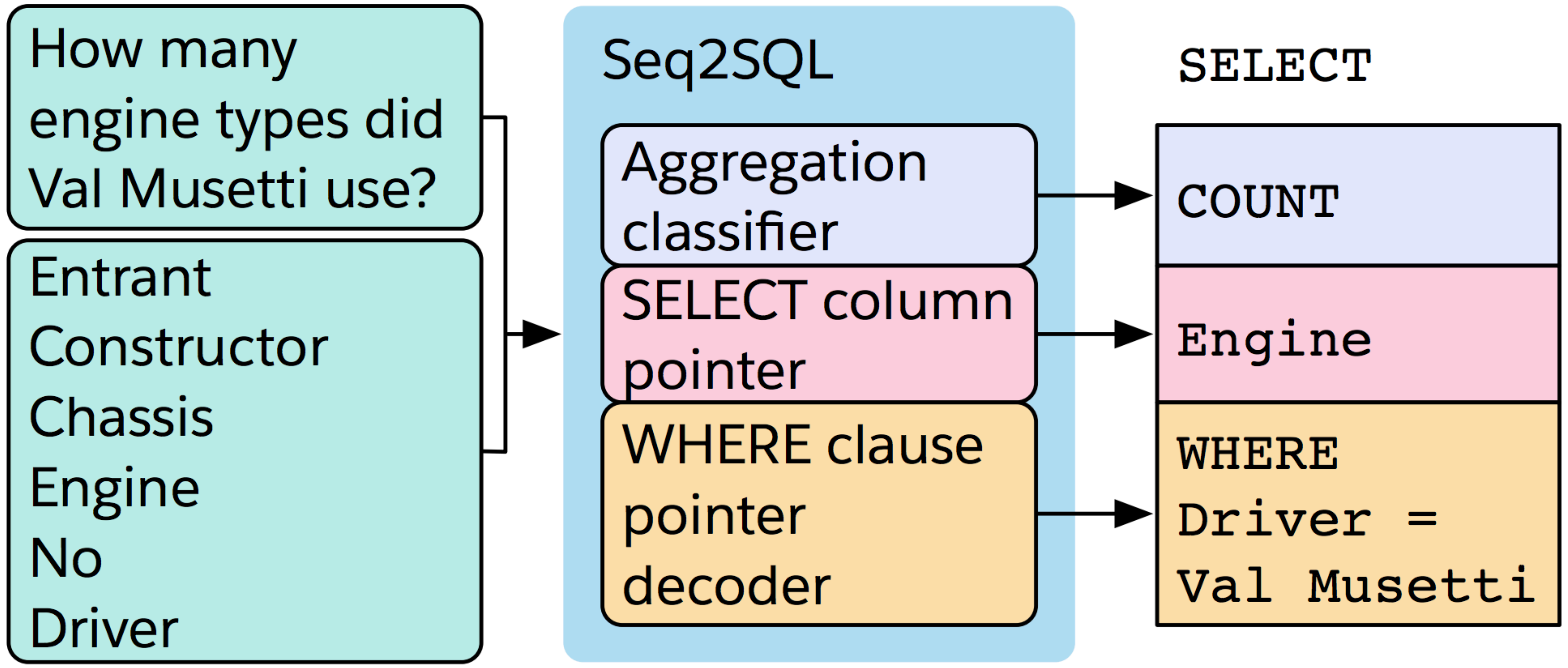

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- How to ensure that well-formed SQL is generated?

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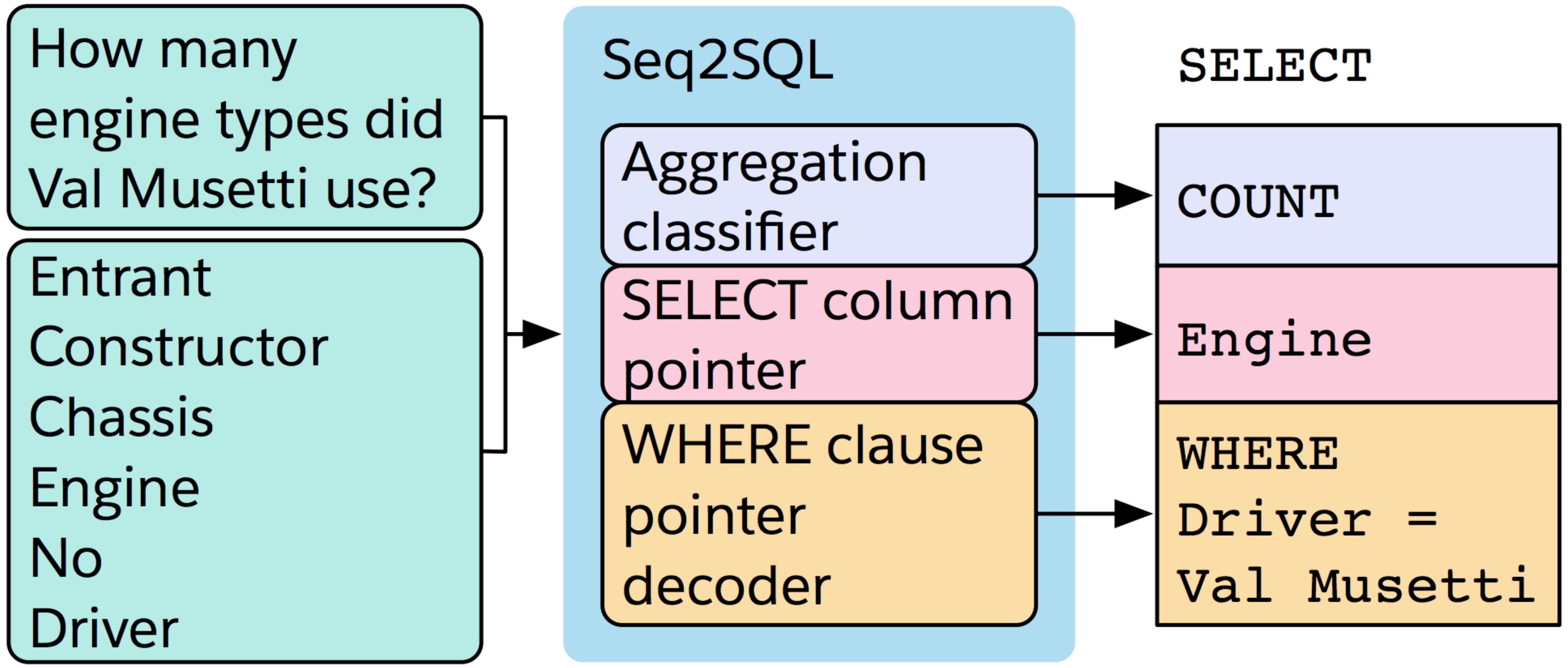
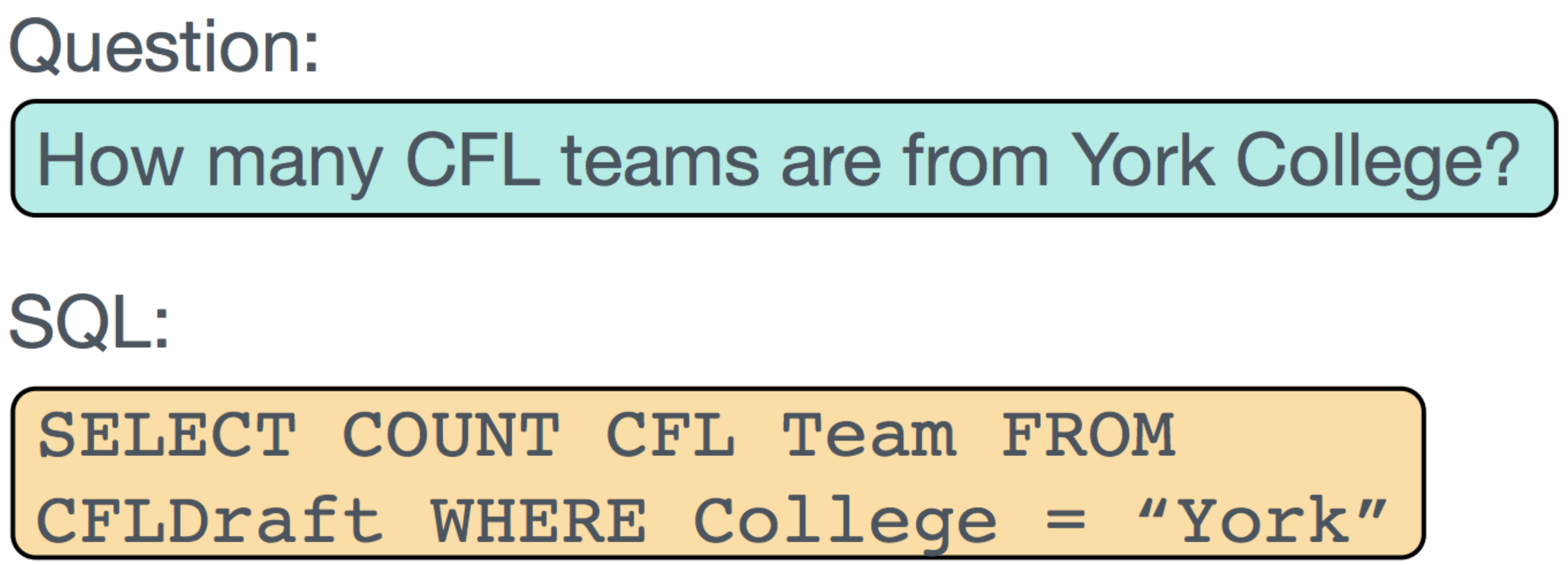


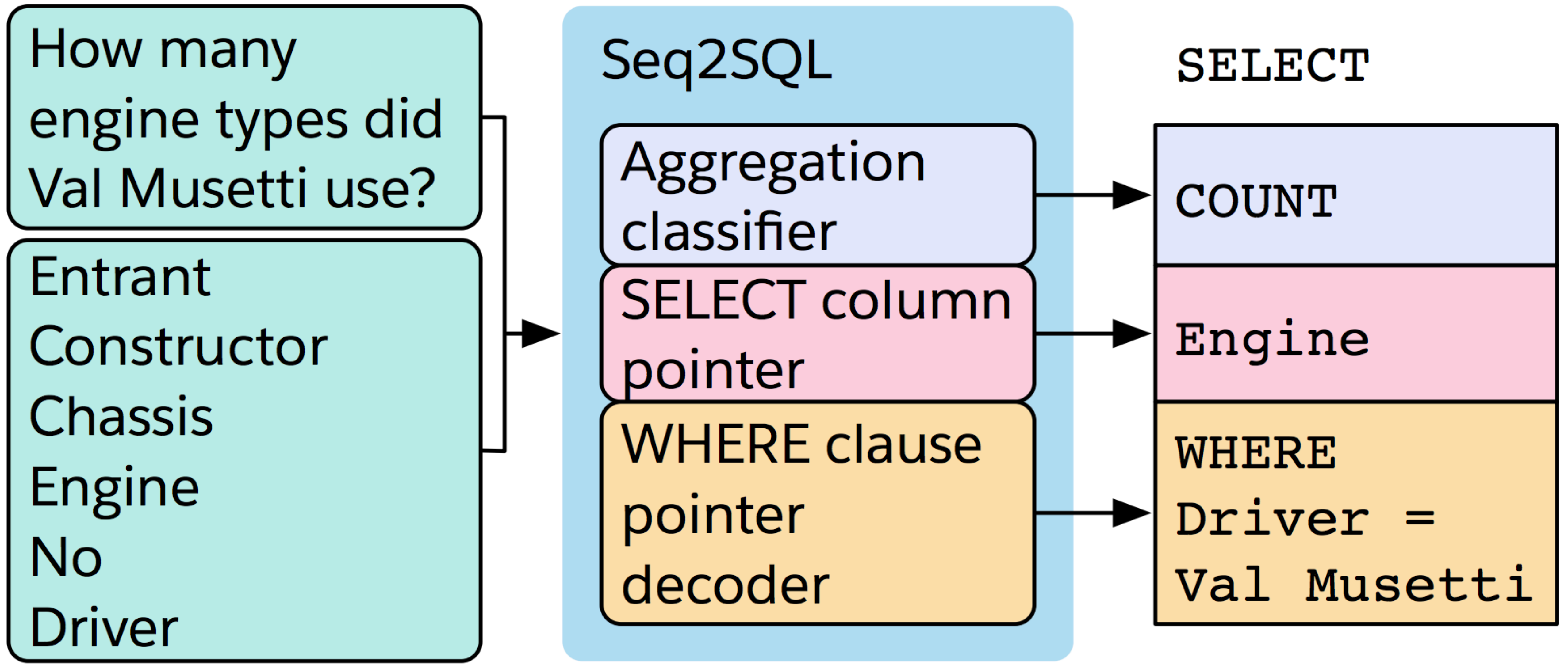
Zhong et al. (2017)

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





Zhong et al. (2017)

SQL Generation

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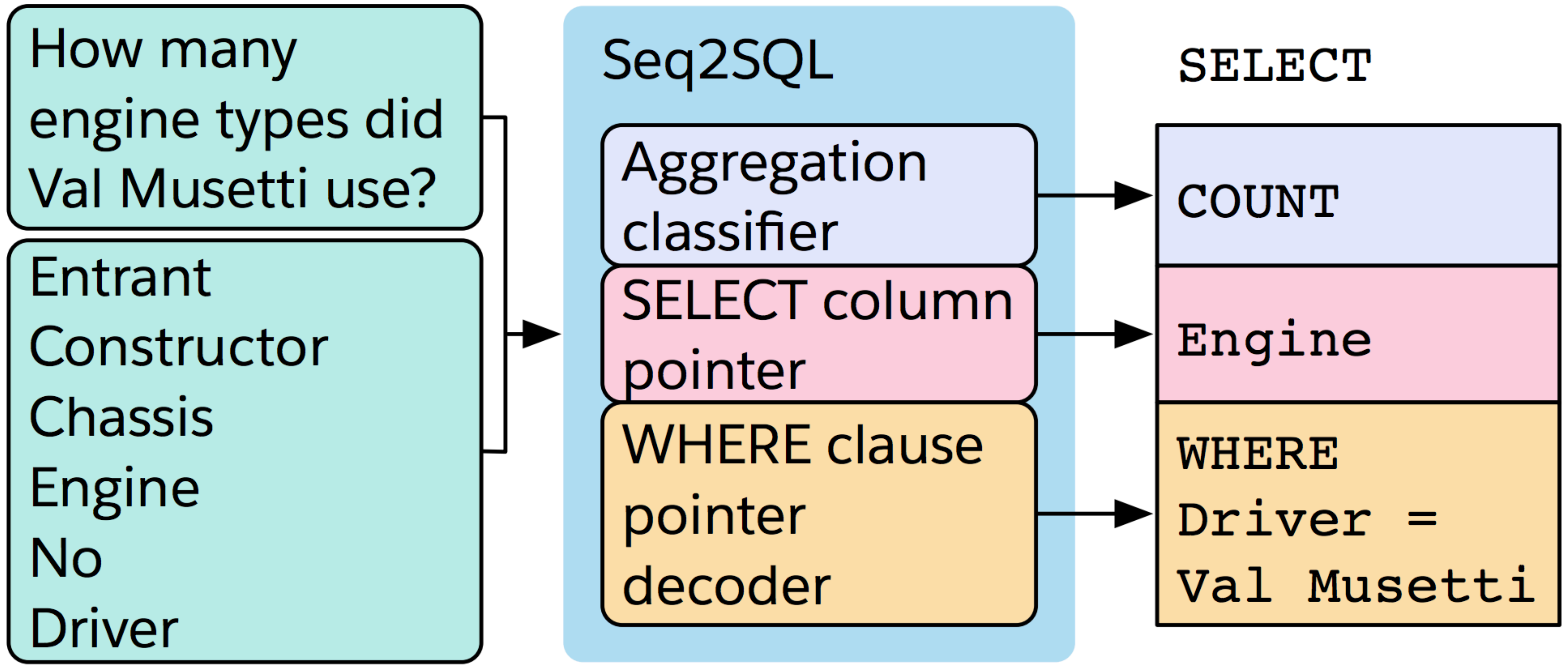
- How to capture column names + constants?

Question:

How many CFL teams are from York College?

SQL:

```
SELECT COUNT CFL Team FROM
CFLDraft WHERE College = “York”
```



Zhong et al. (2017)

SQL Generation

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- How to capture column names + constants?
  - Pointer mechanisms

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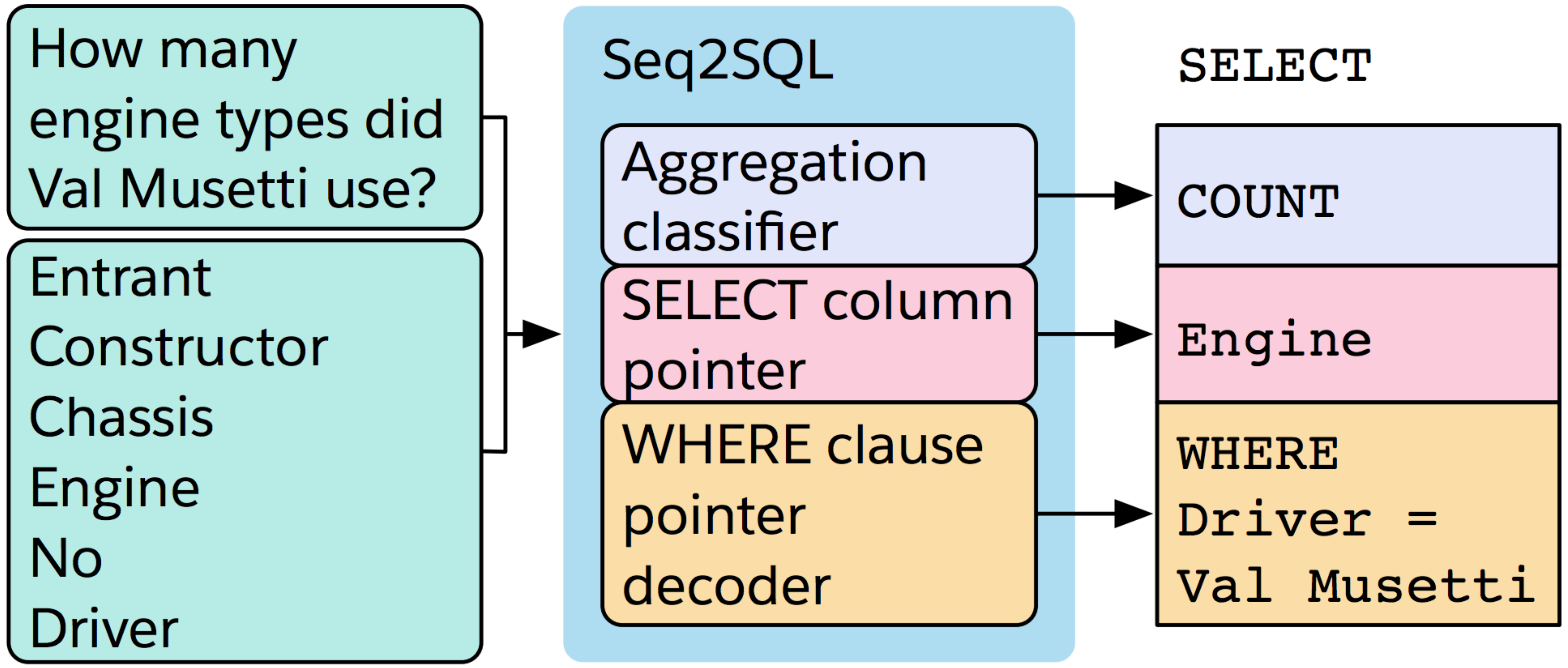

Zhong et al. (2017)

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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Problems with Seq2seq Models

- Encoder-decoder models like to repeat themselves:

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

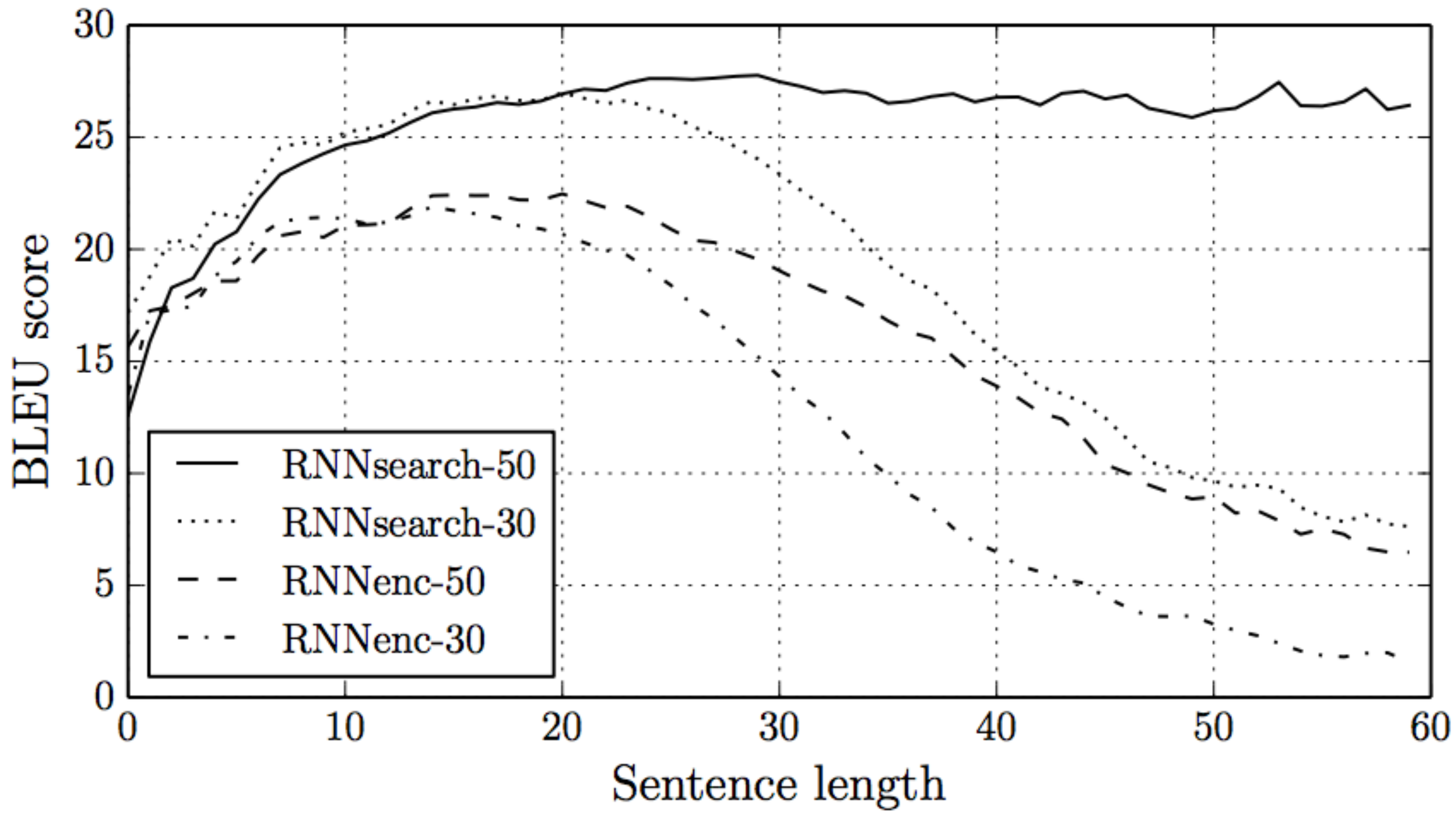
fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] . . . , a été *démonté* jeudi matin

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

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

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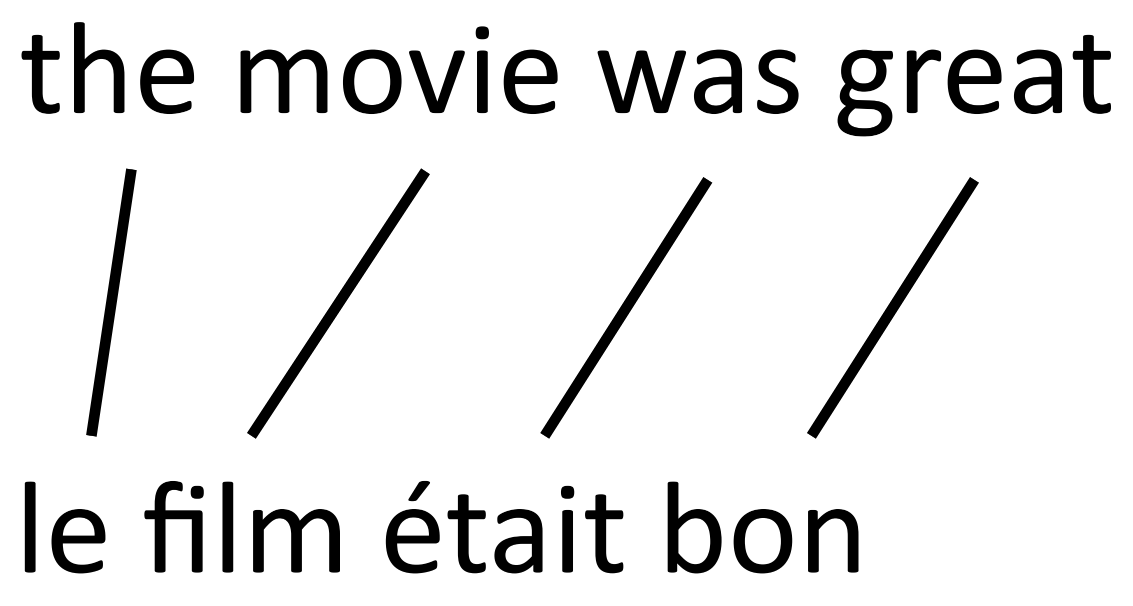

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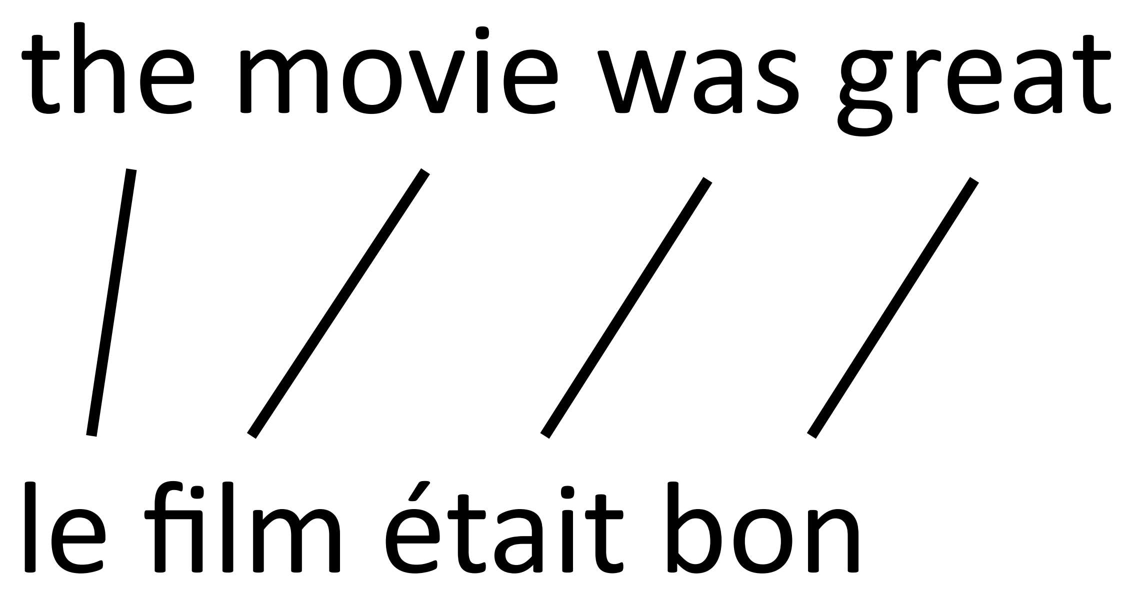

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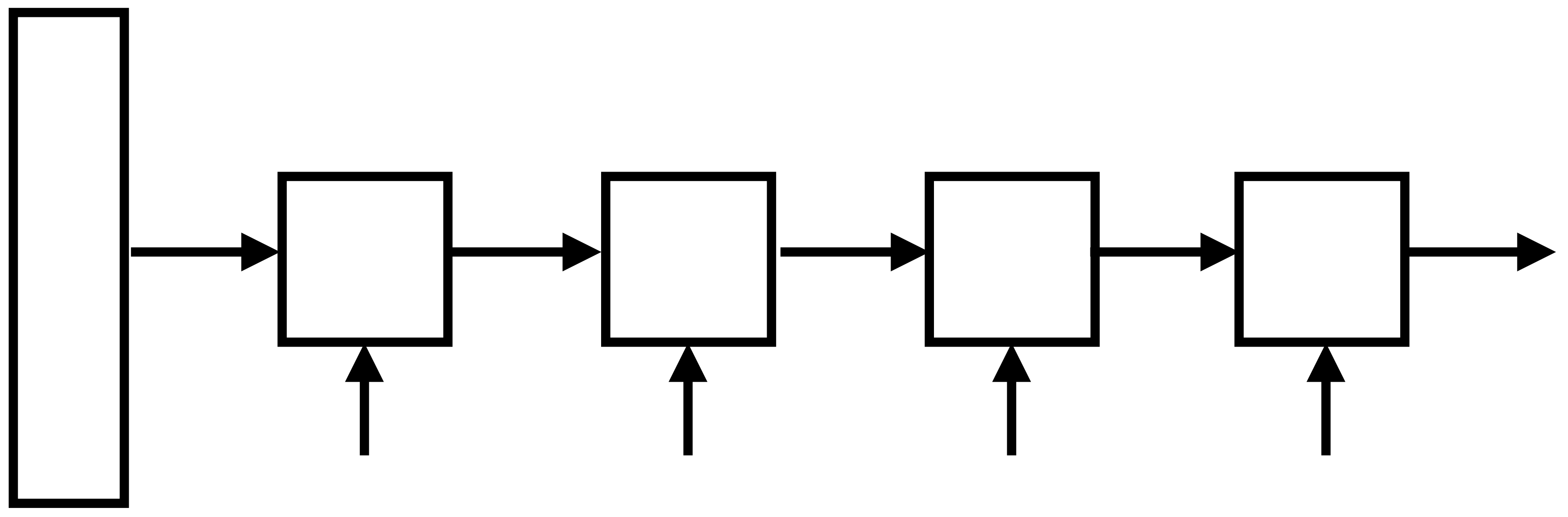

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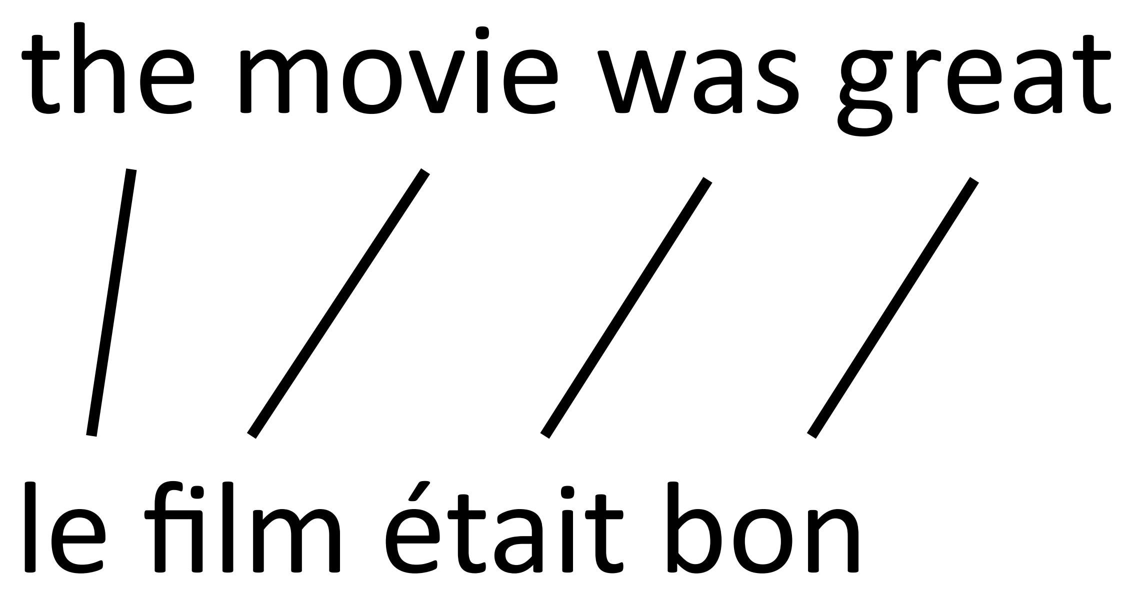

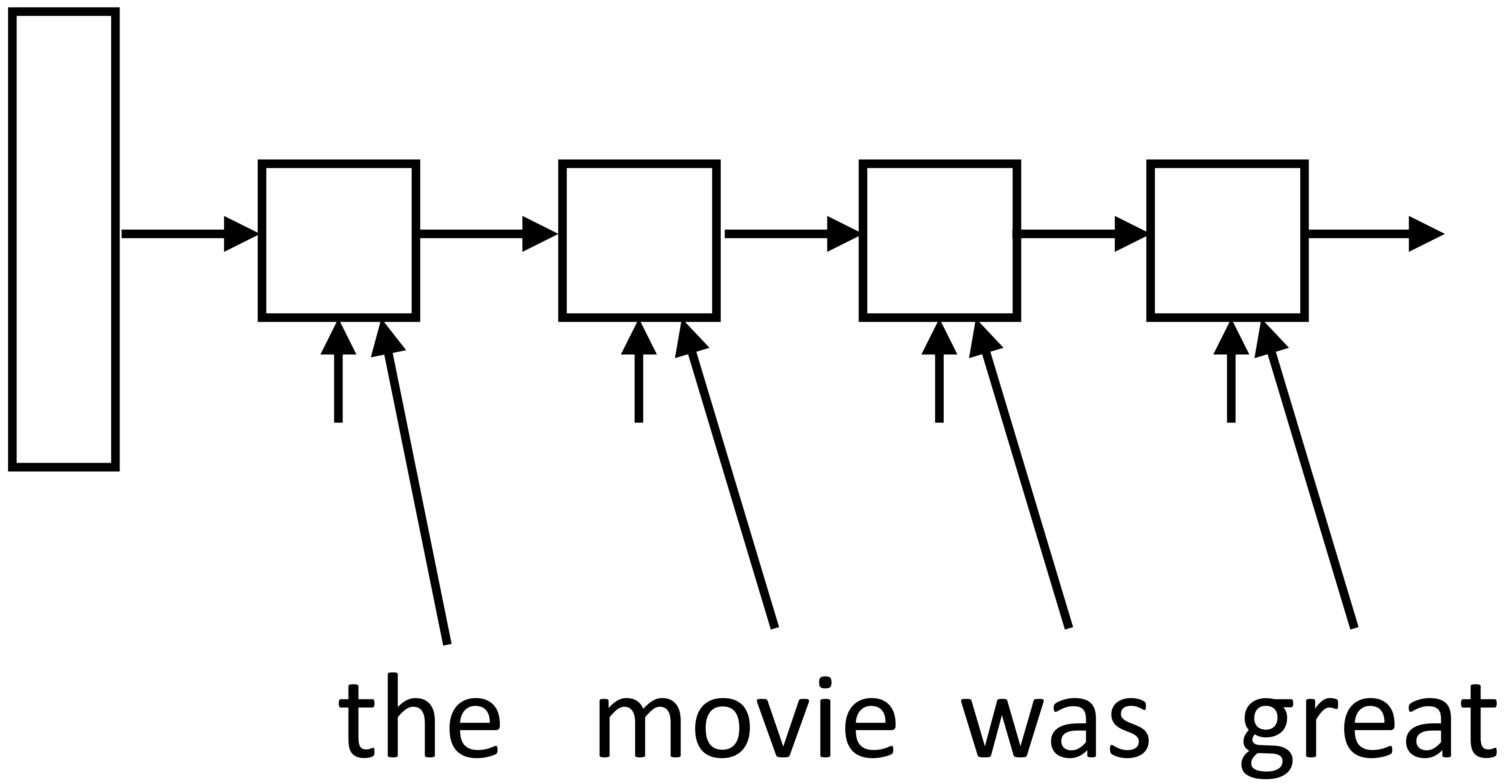

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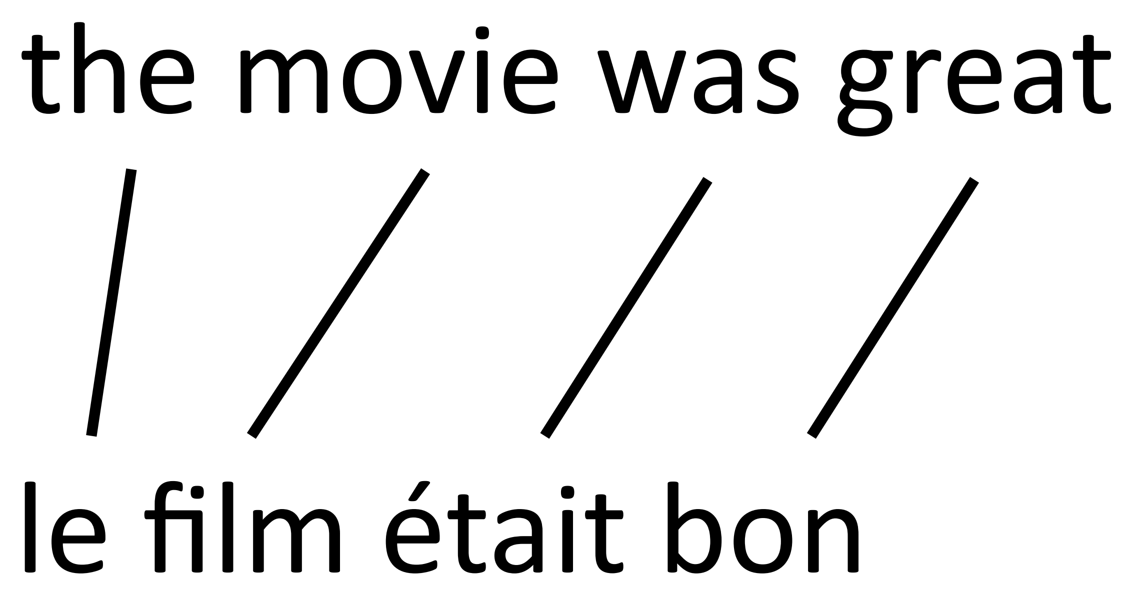

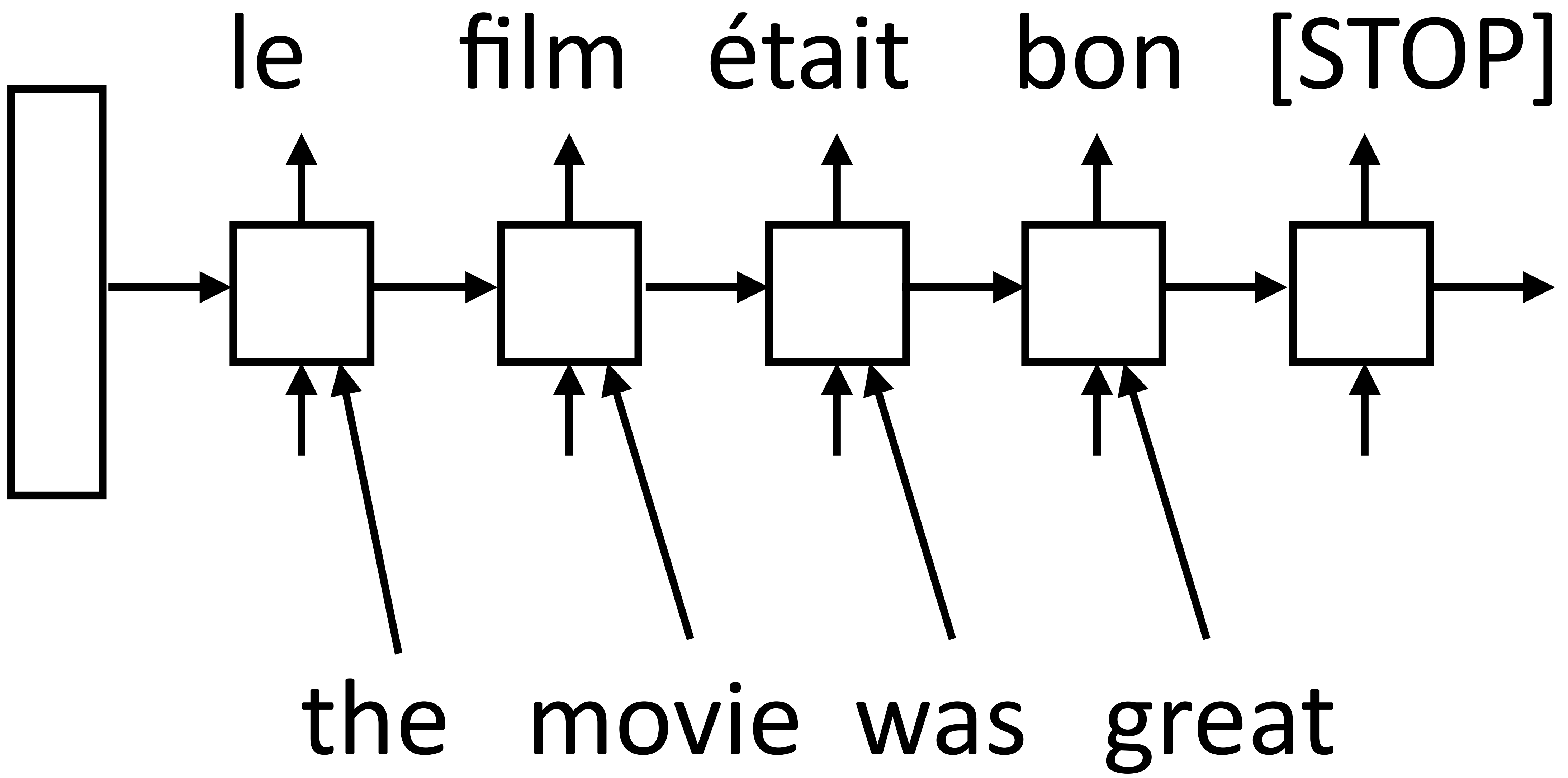

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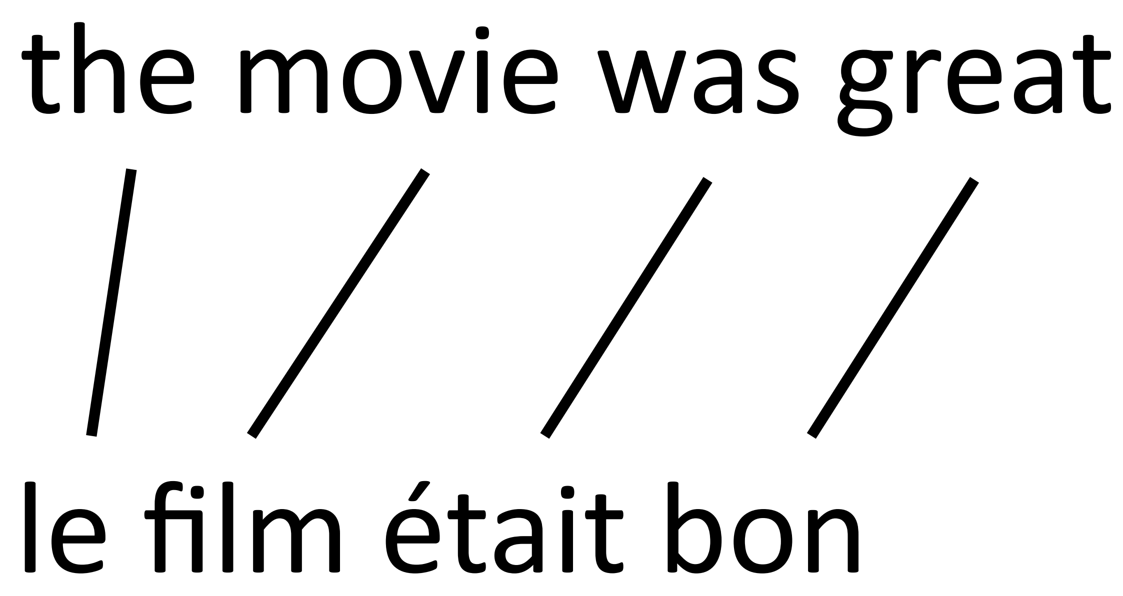
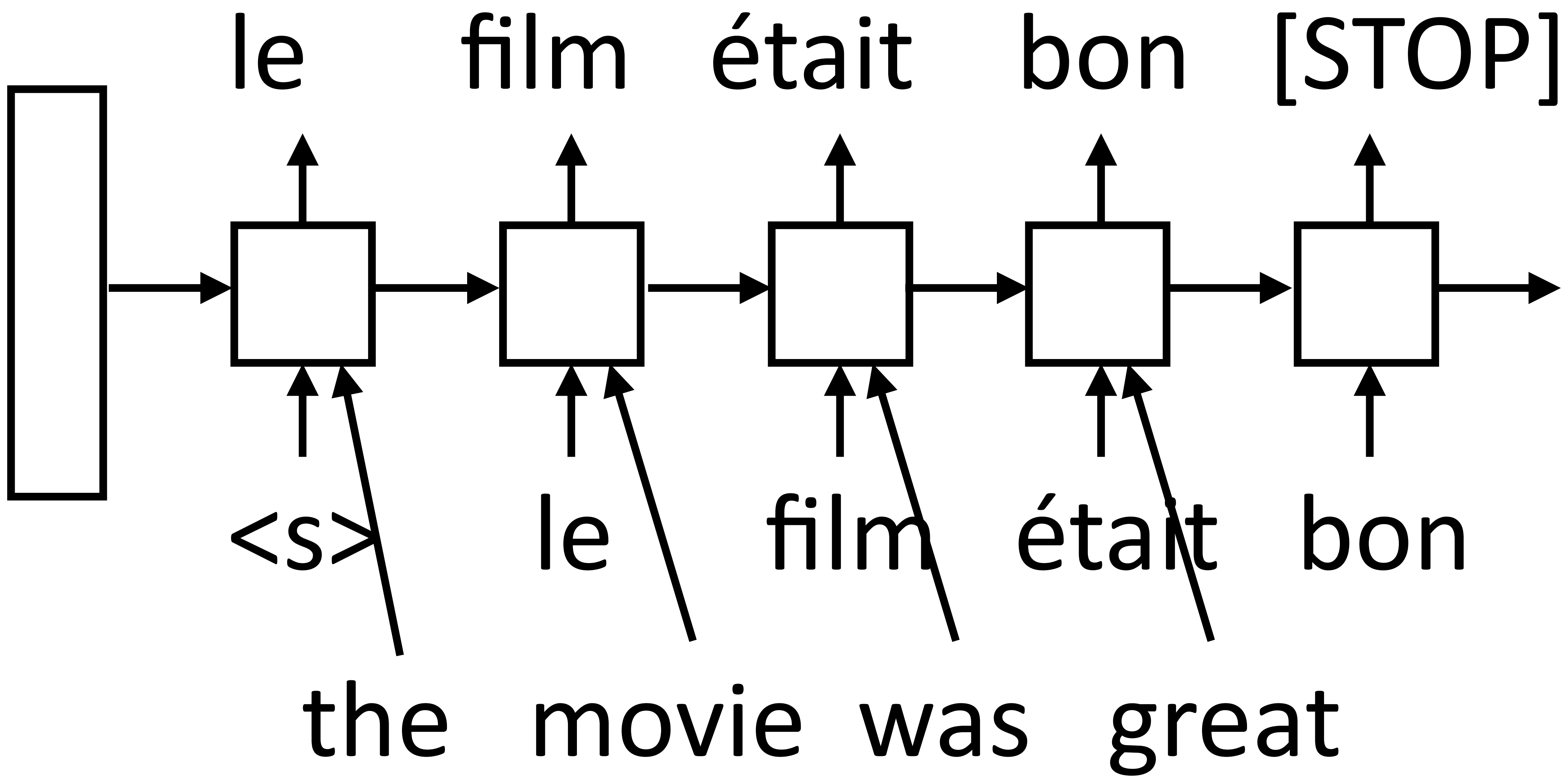
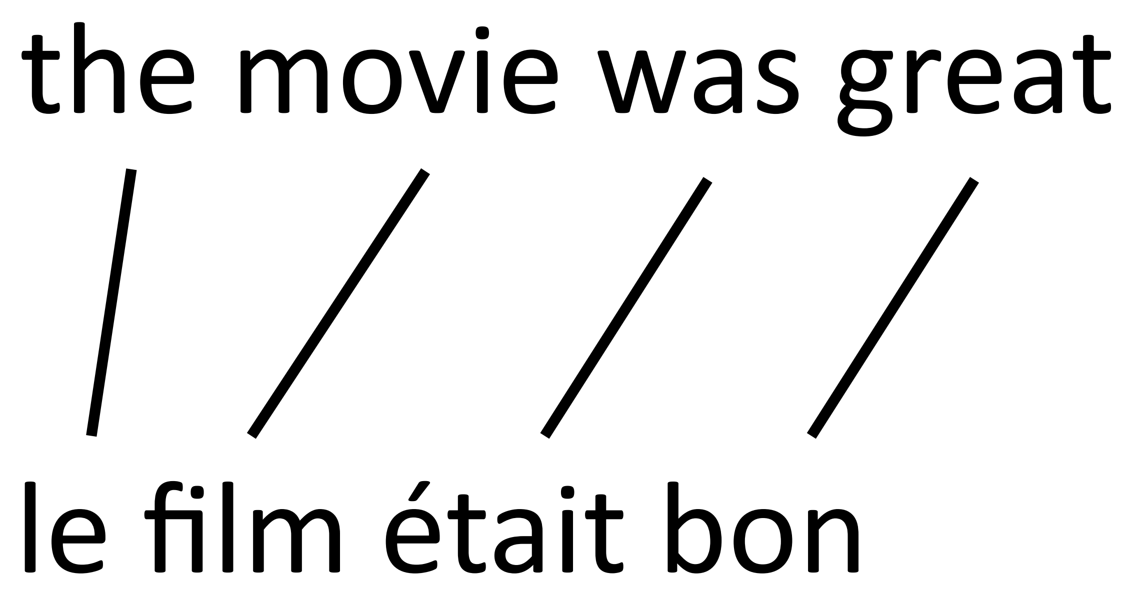
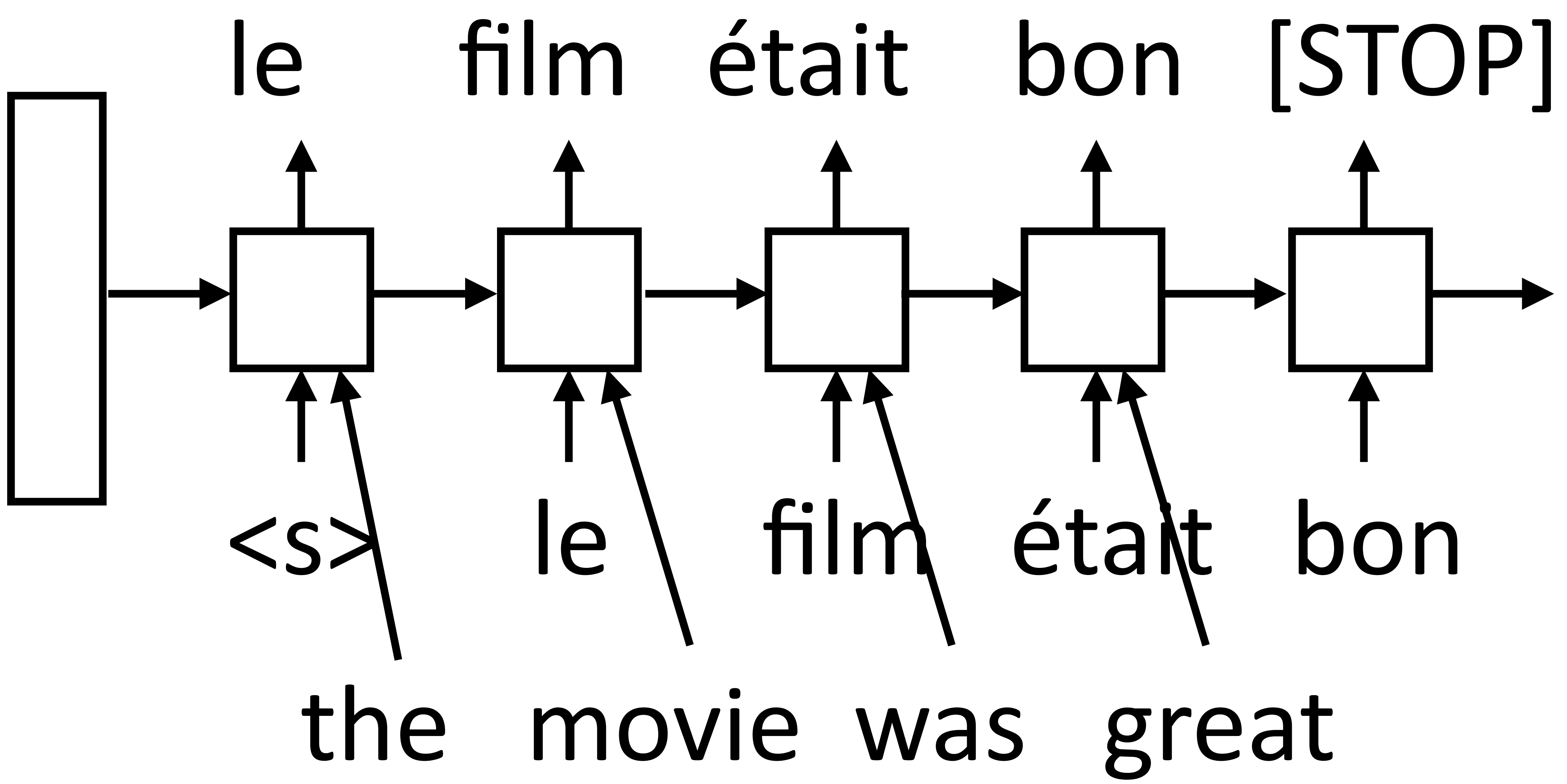




Aligned Inputs

- 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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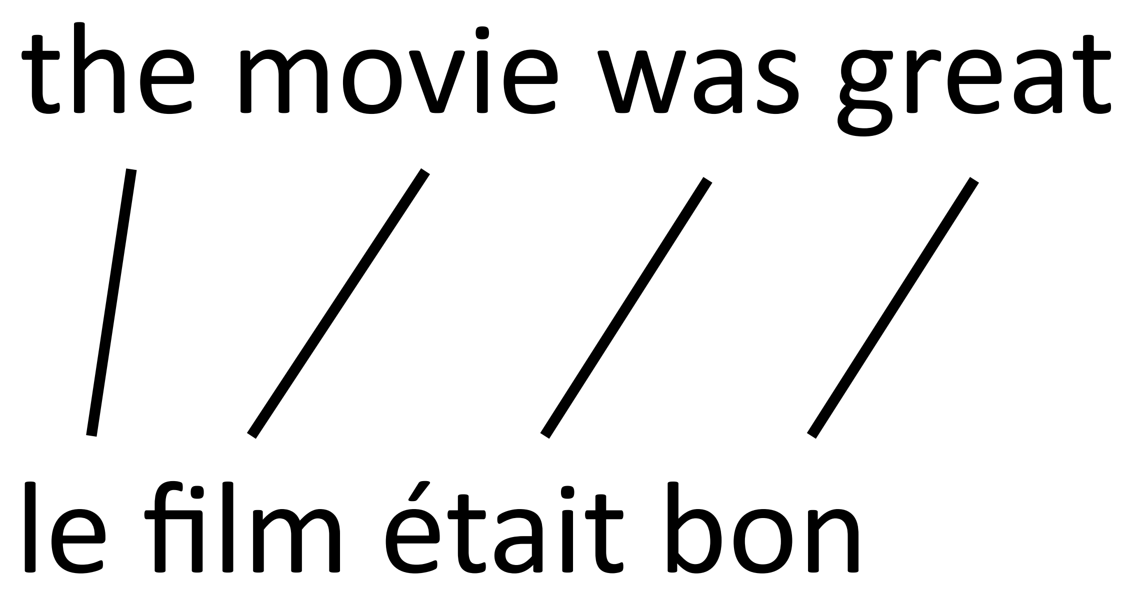

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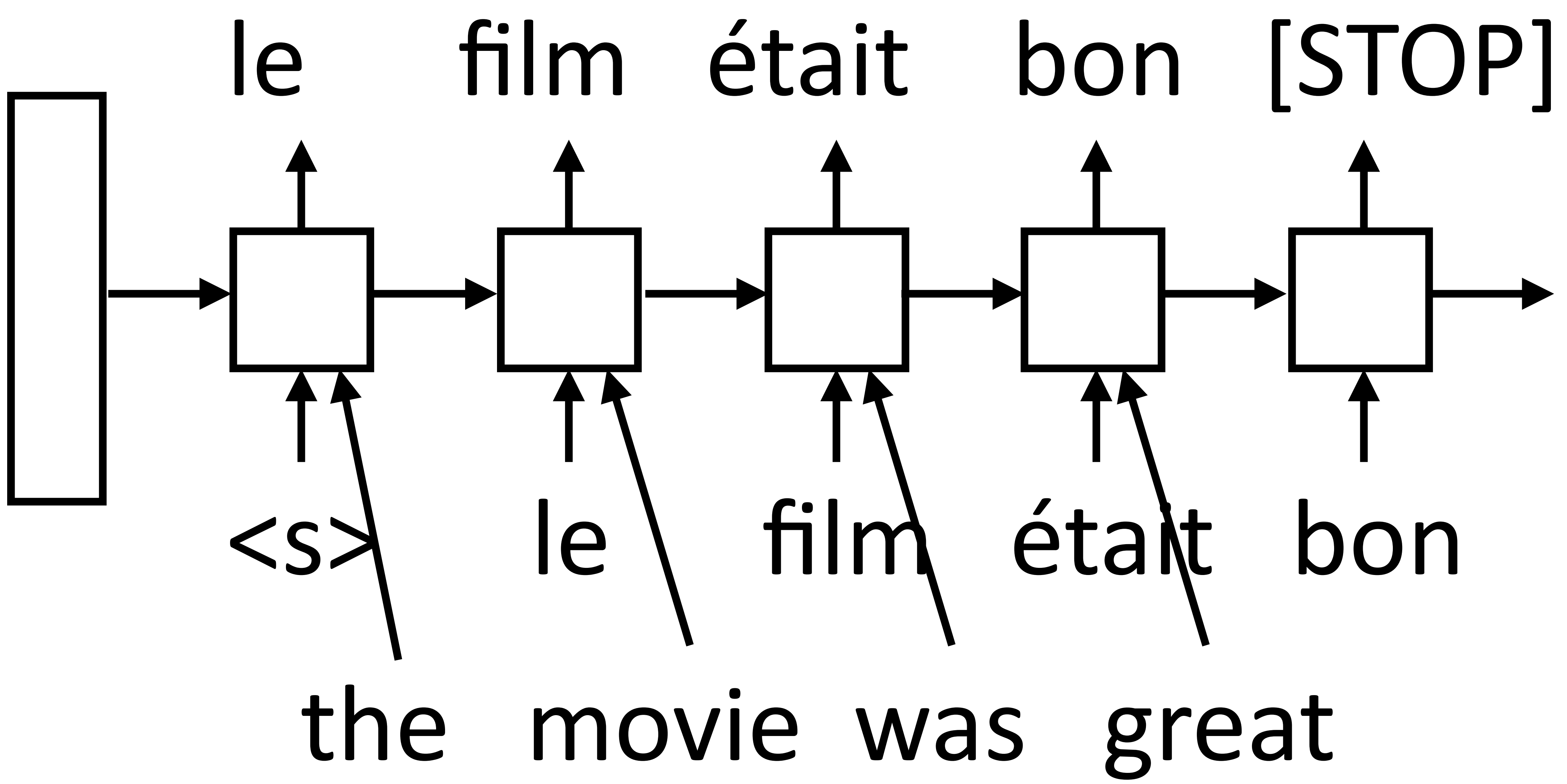
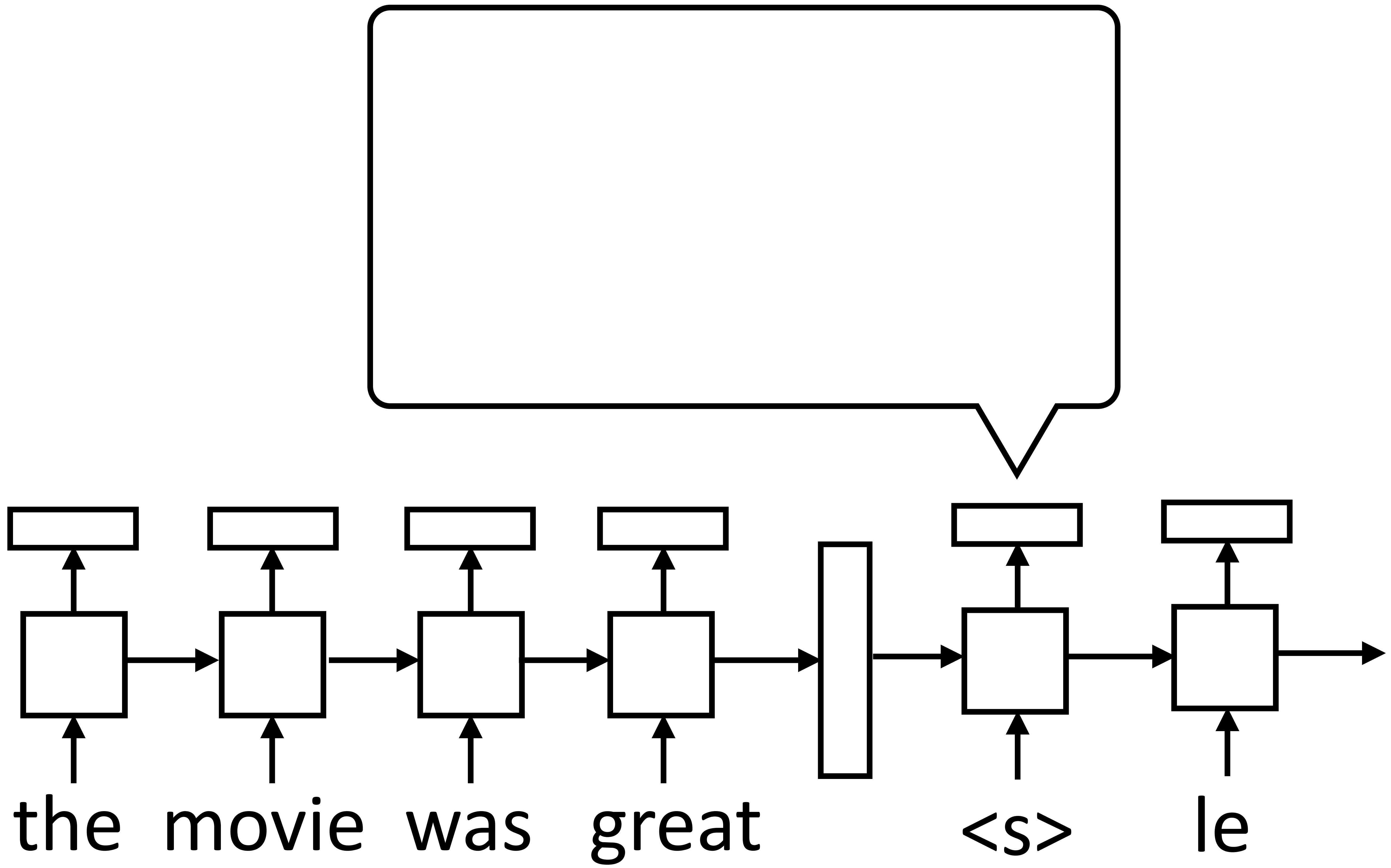


- Much less burden on the hidden state

- How can we achieve this without hardcoding it?

Attention



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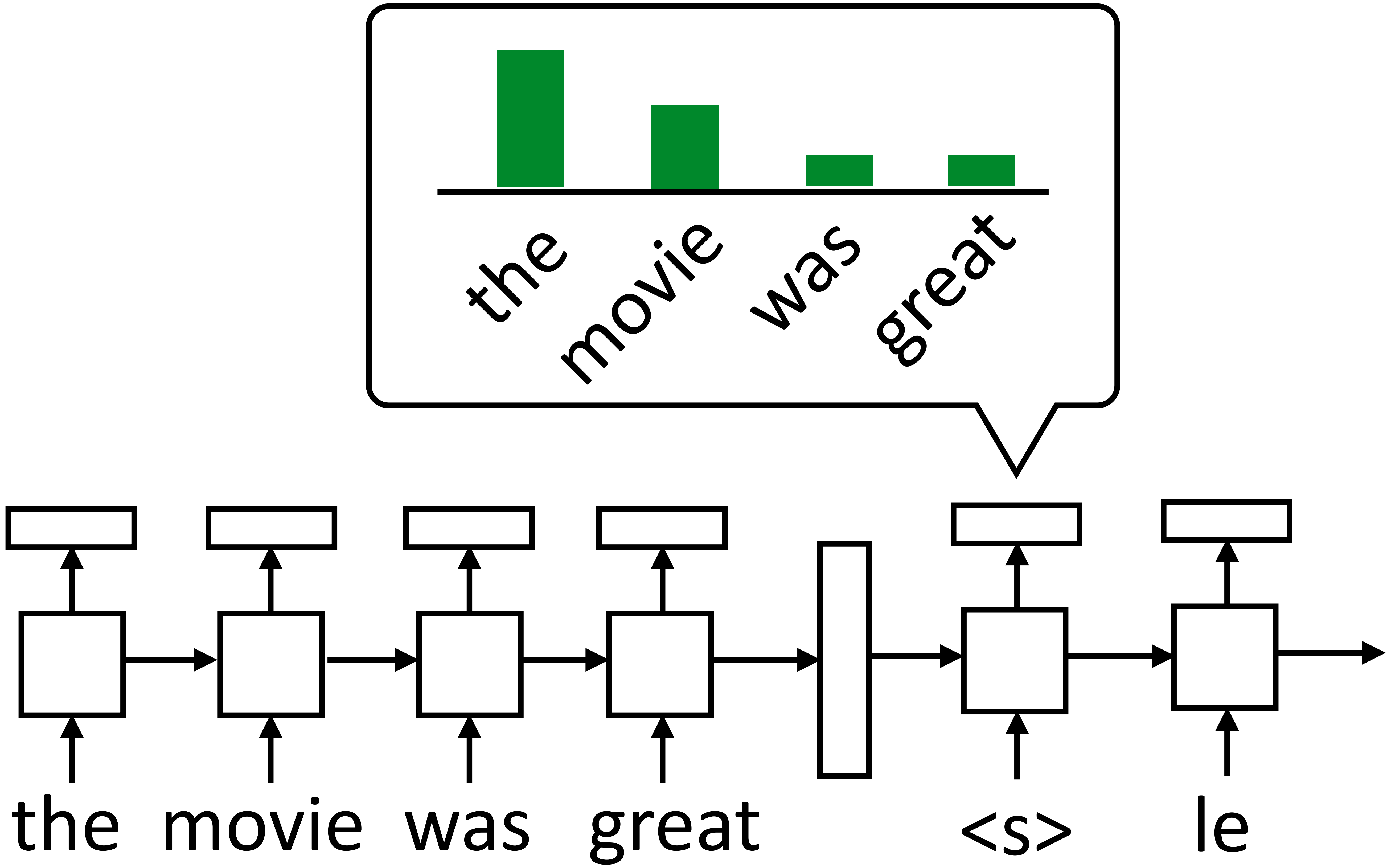

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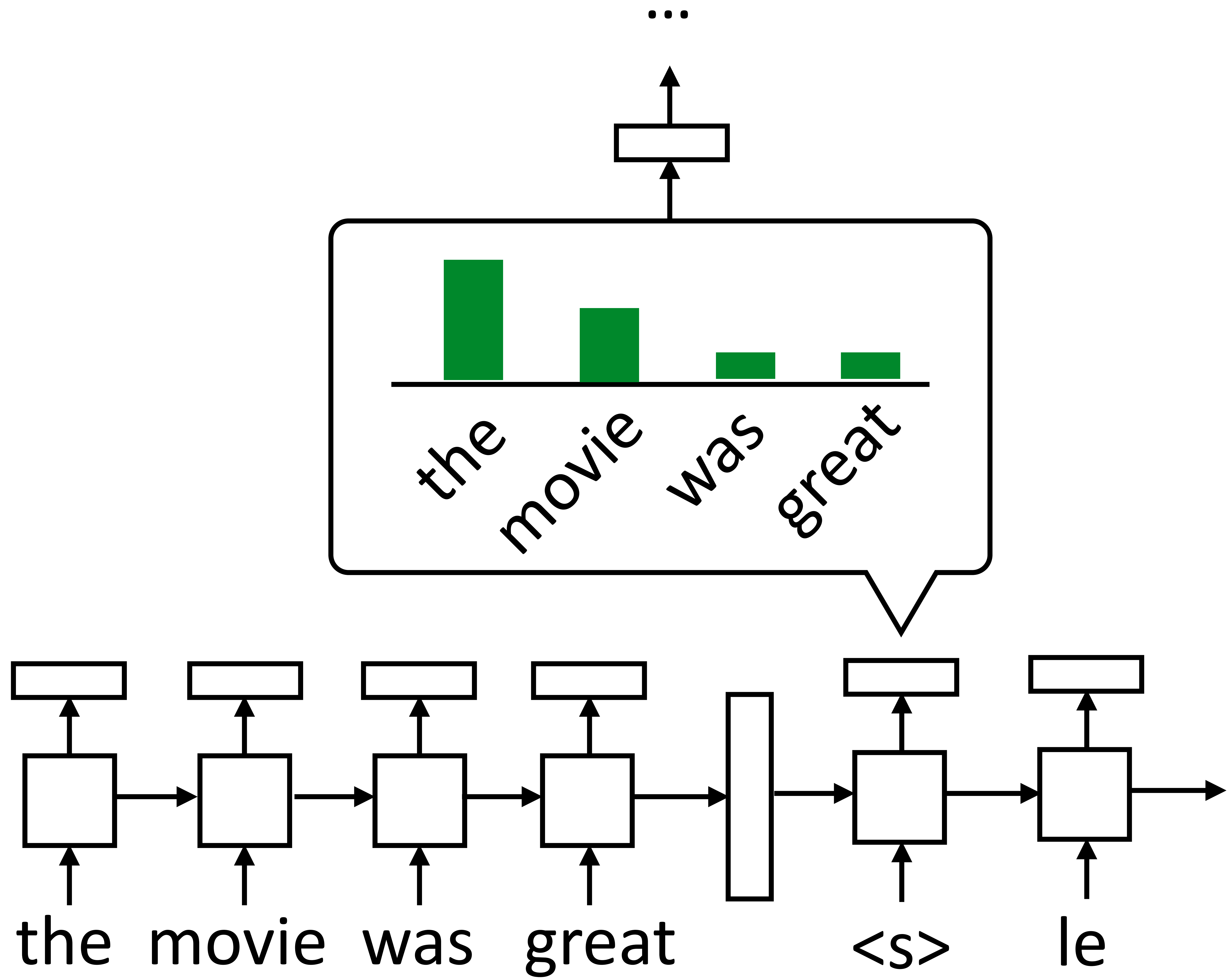

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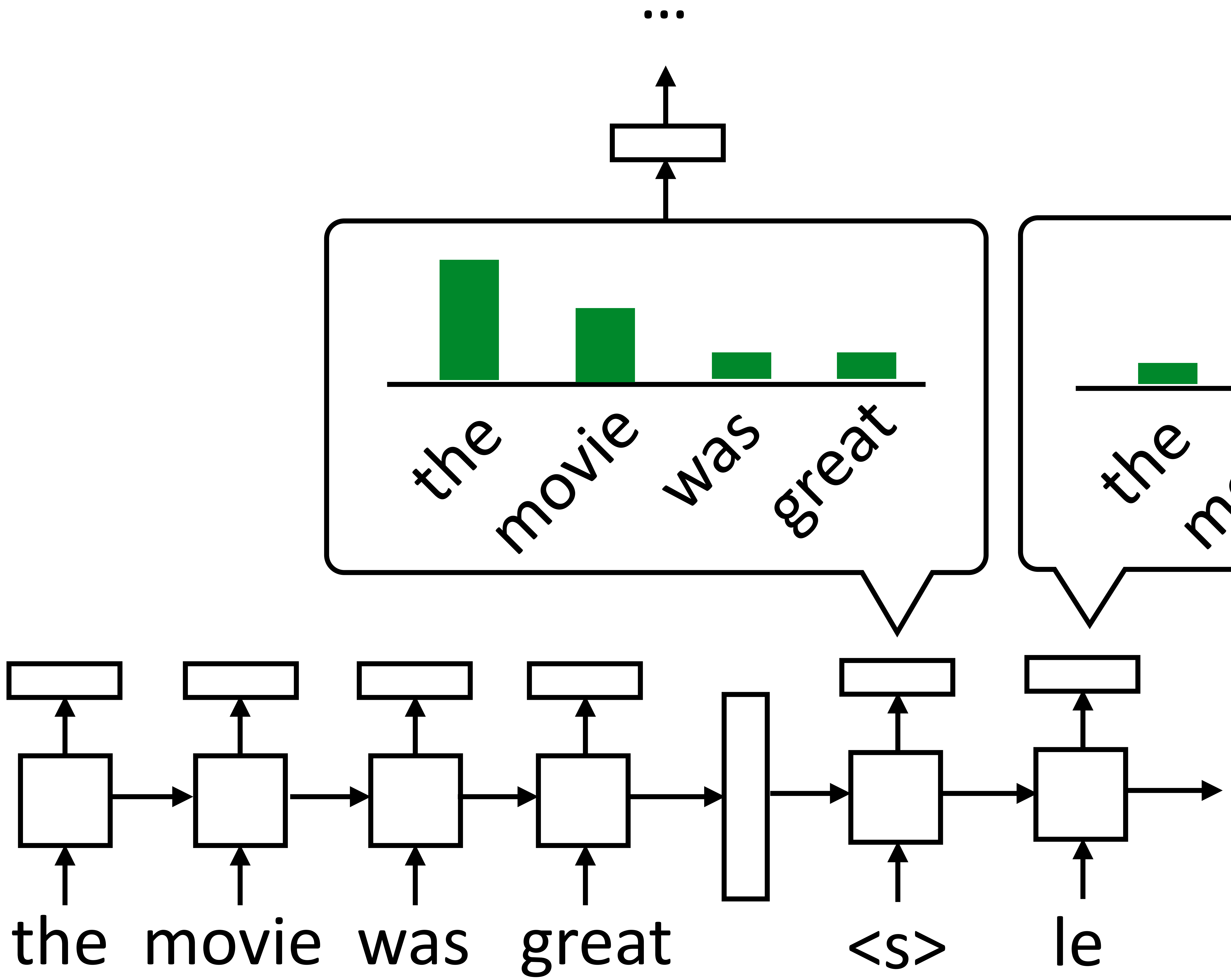

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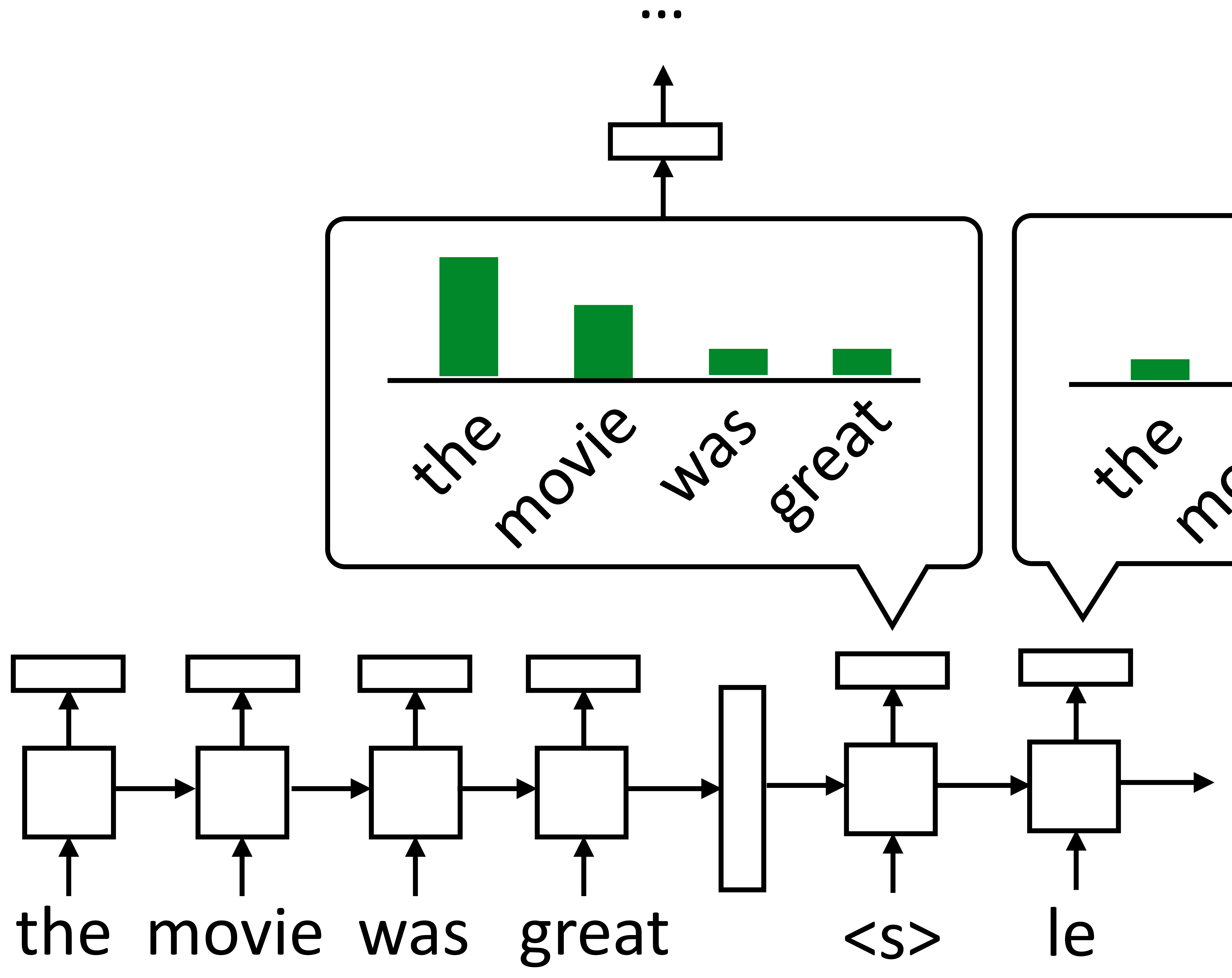

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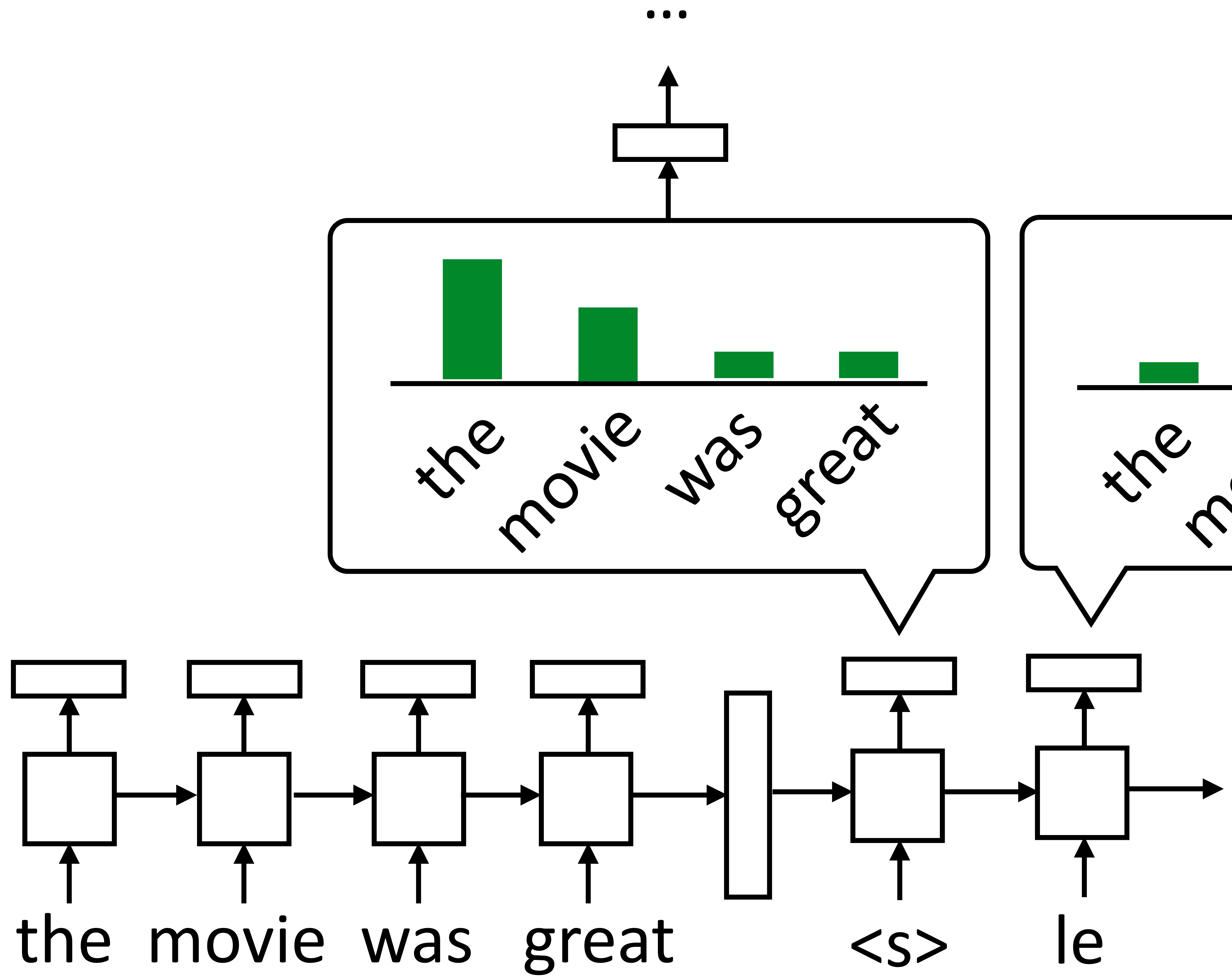

- At each decoder state, compute a distribution over source inputs based on current decoder state

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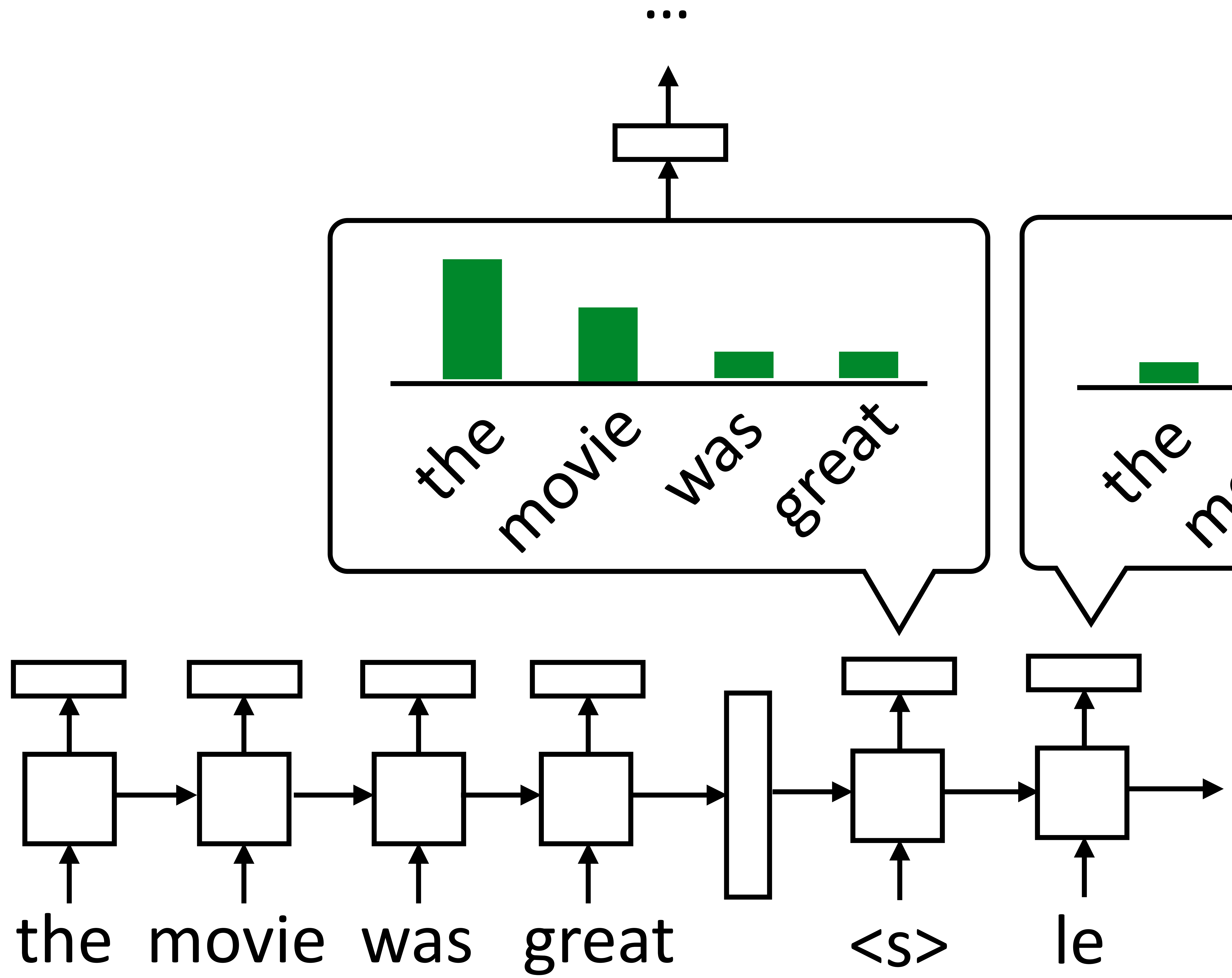
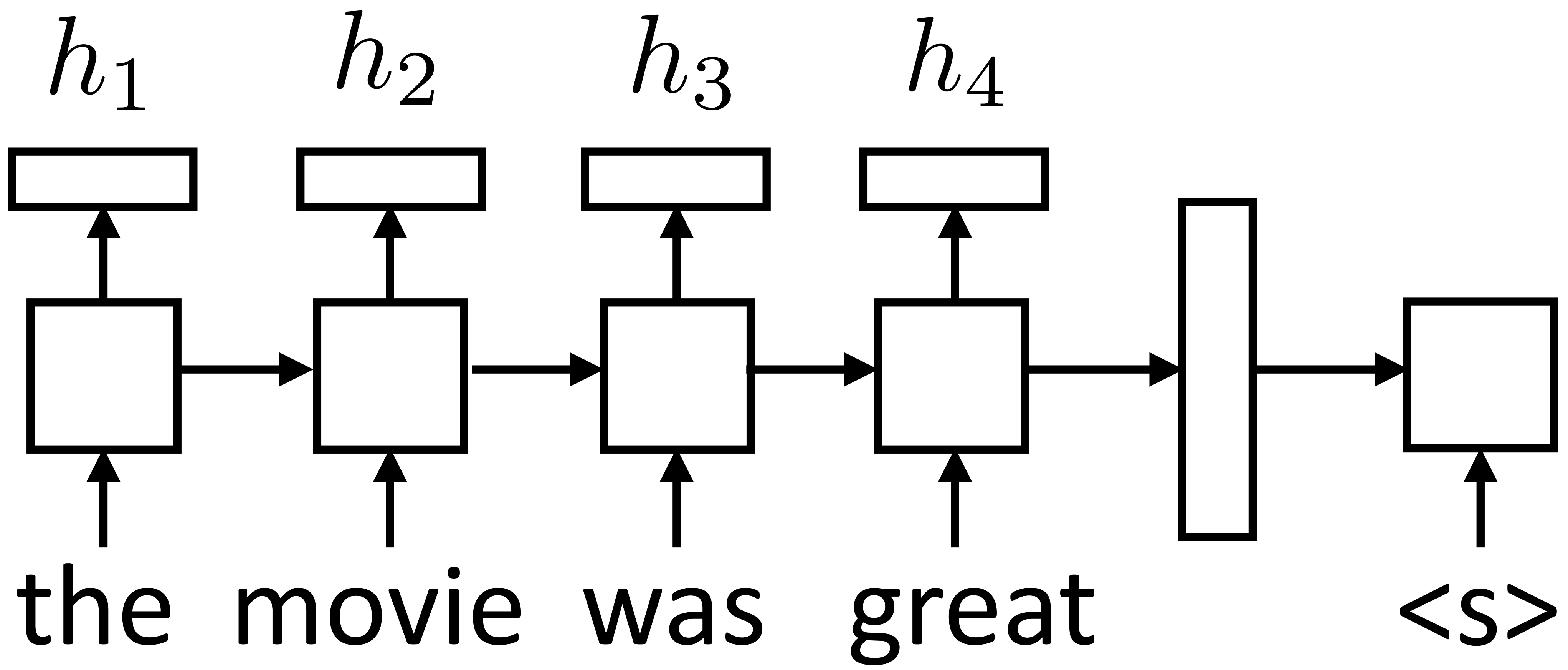


- At each decoder state, compute a distribution over source inputs based on current decoder state
- Use that in output layer

Attention

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



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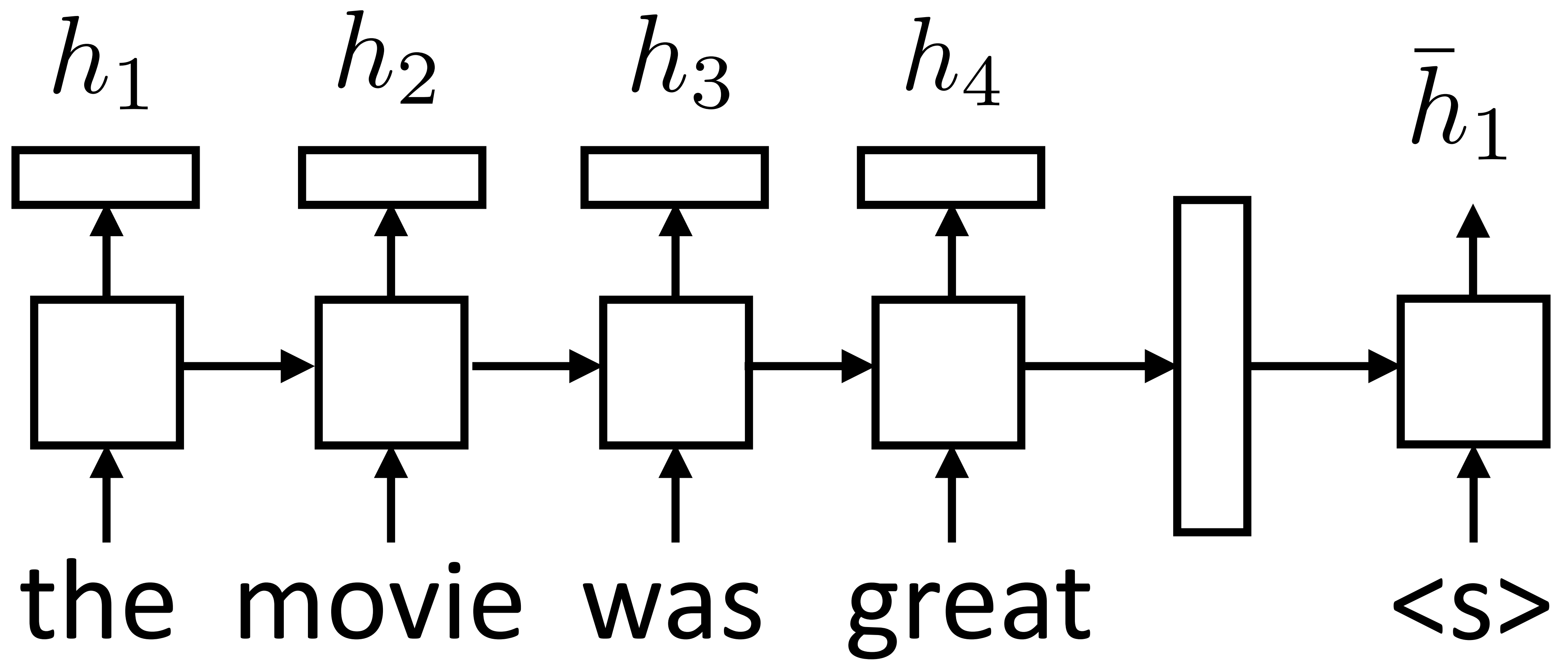

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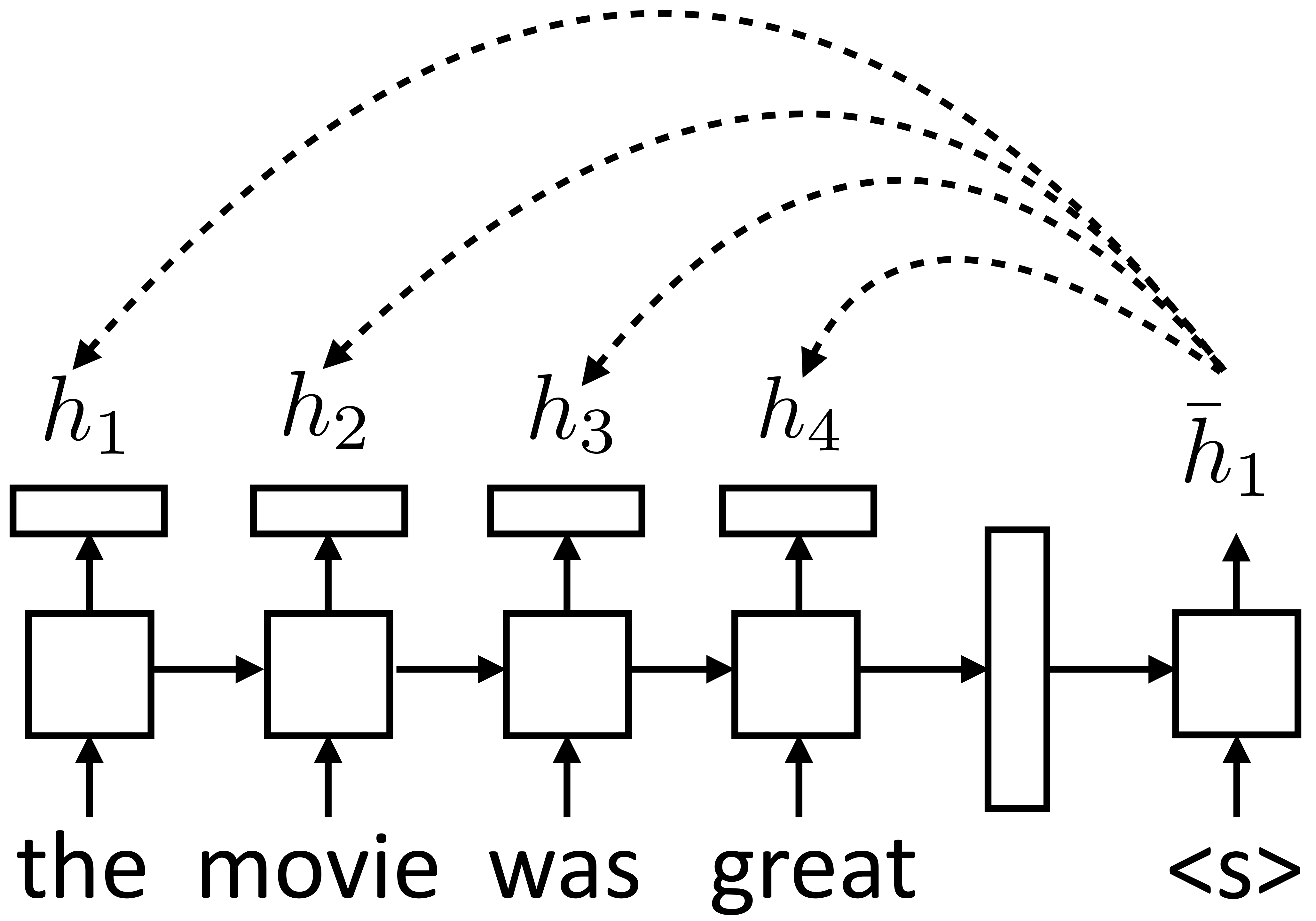

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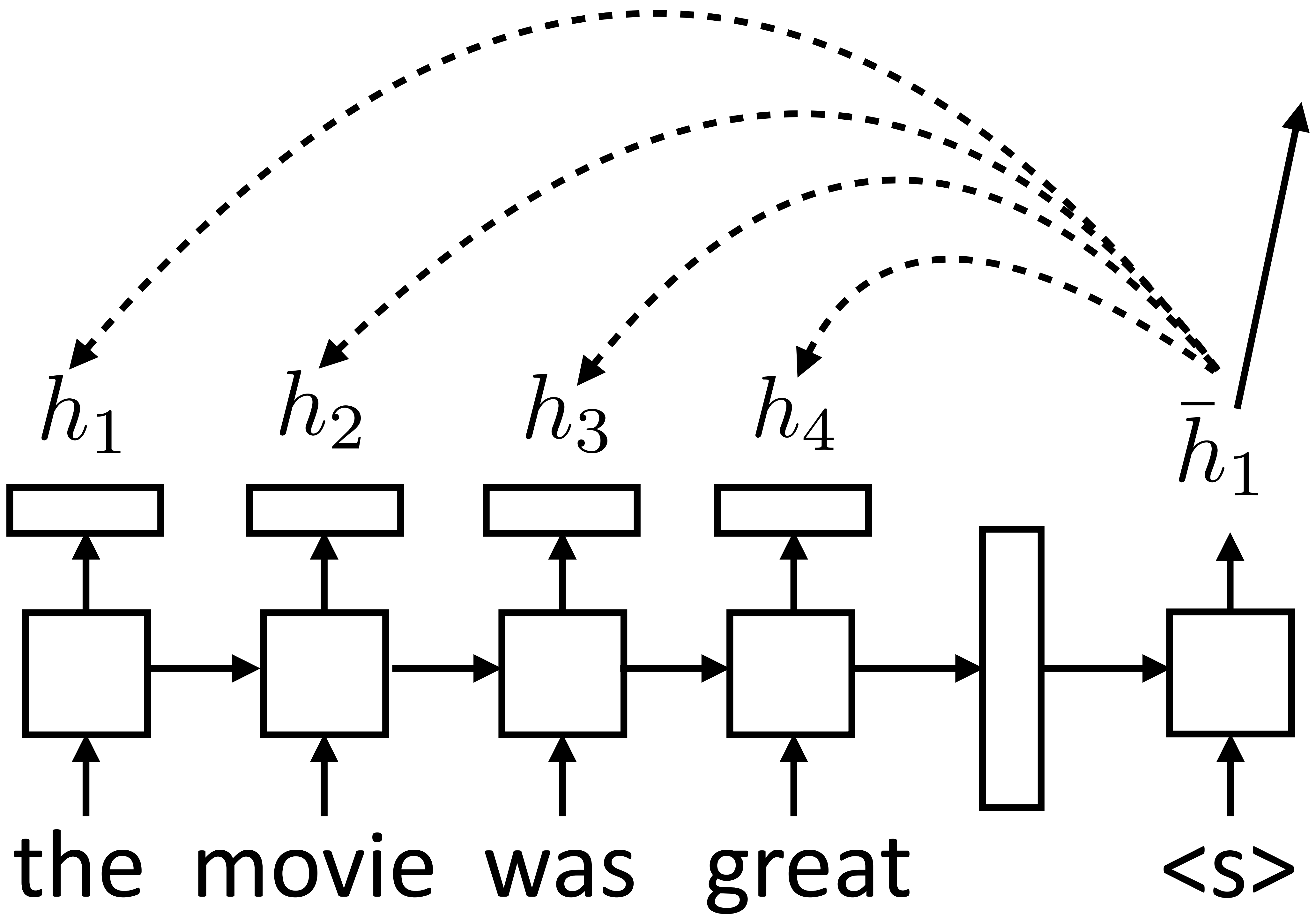

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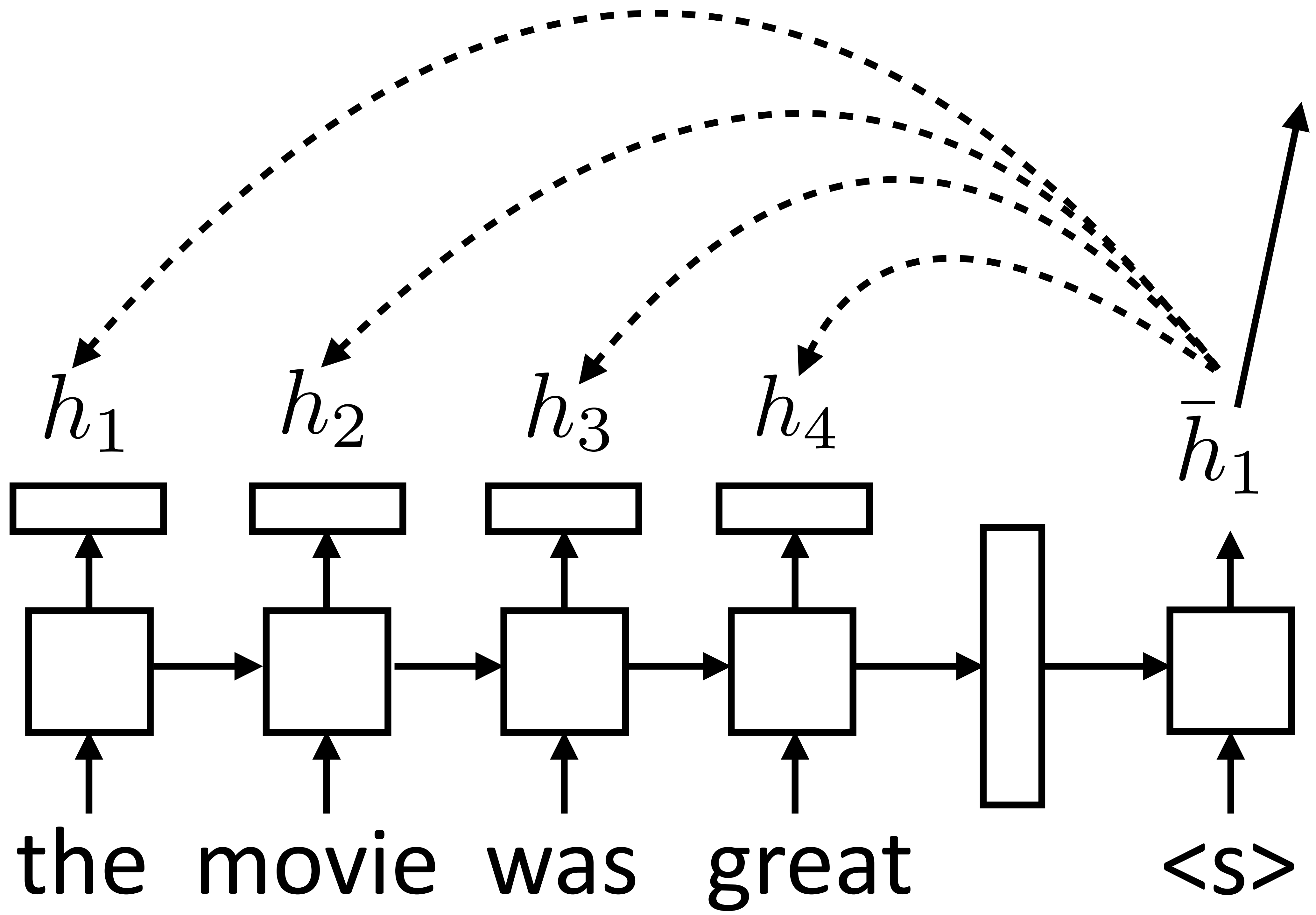

$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

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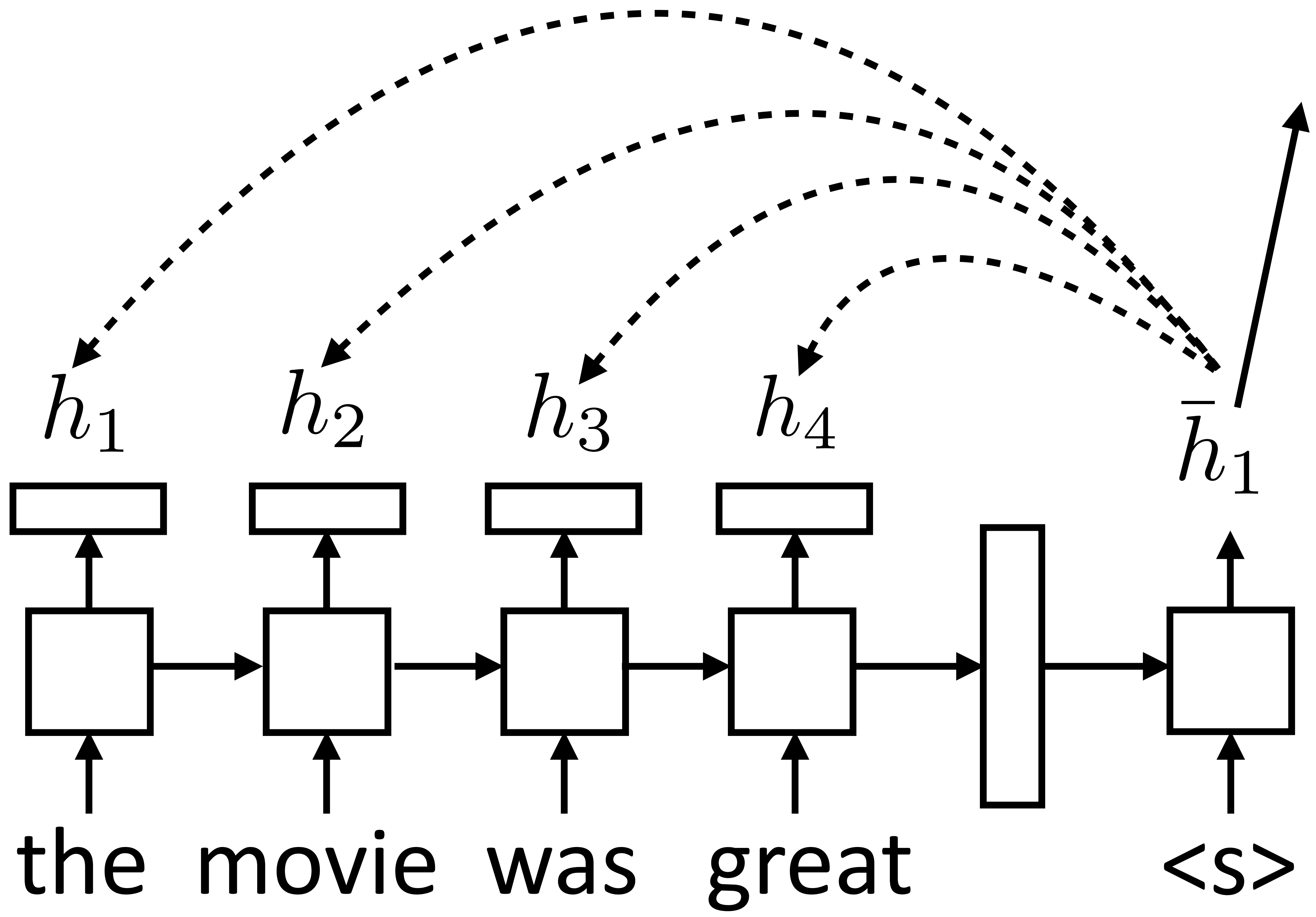
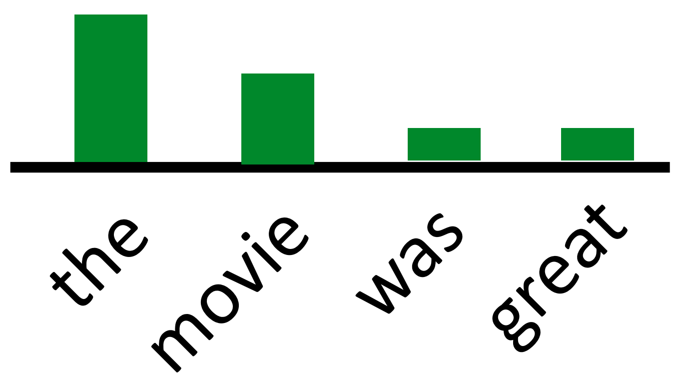


$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$



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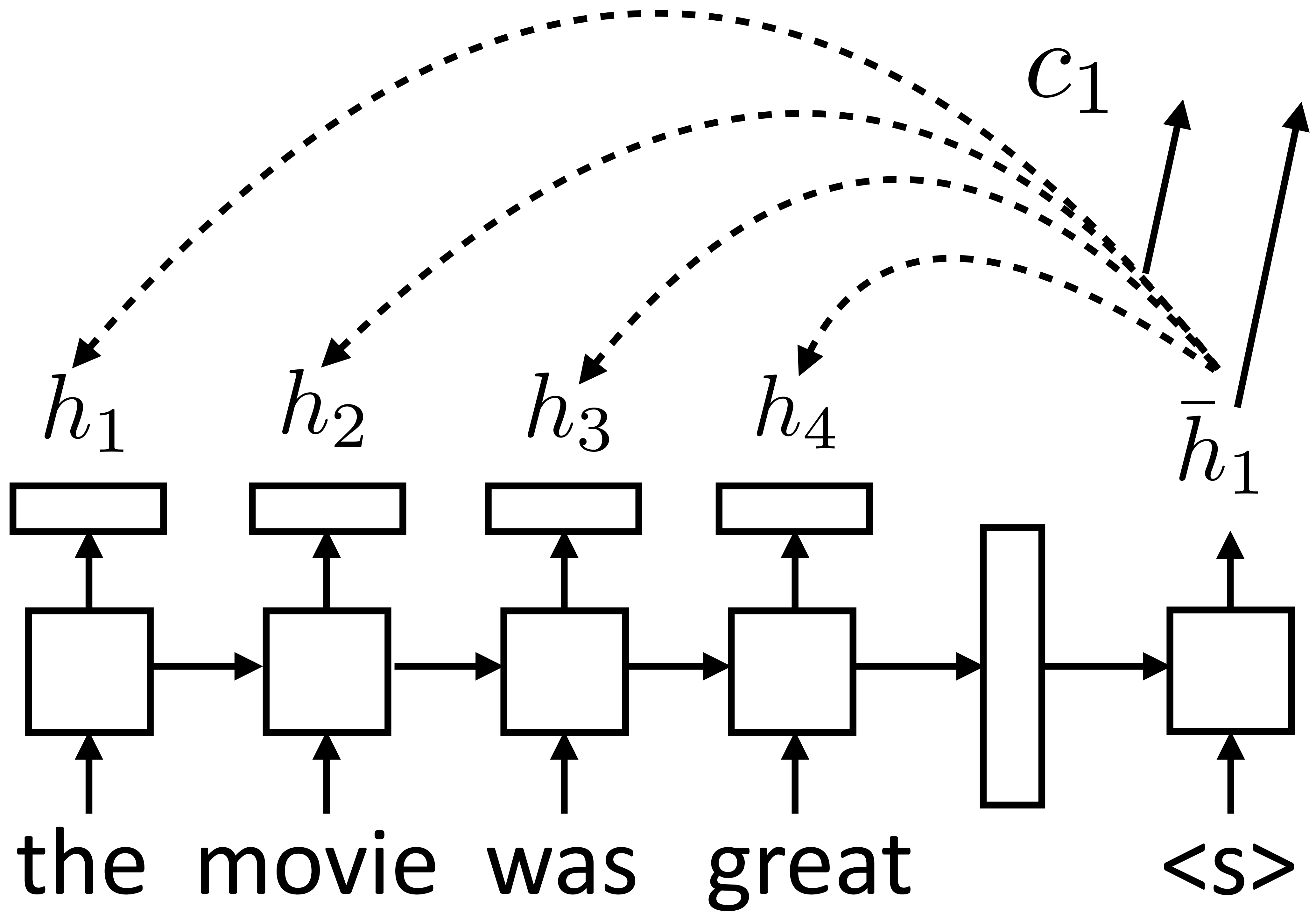

$$c_i = \sum_j \alpha_{ij} h_j$$

- Weighted sum of input hidden states (vector)

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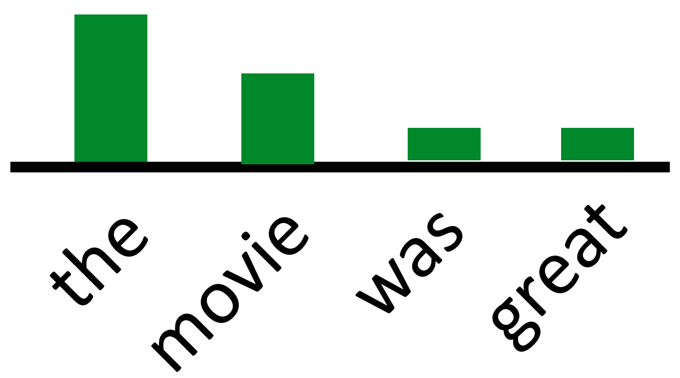

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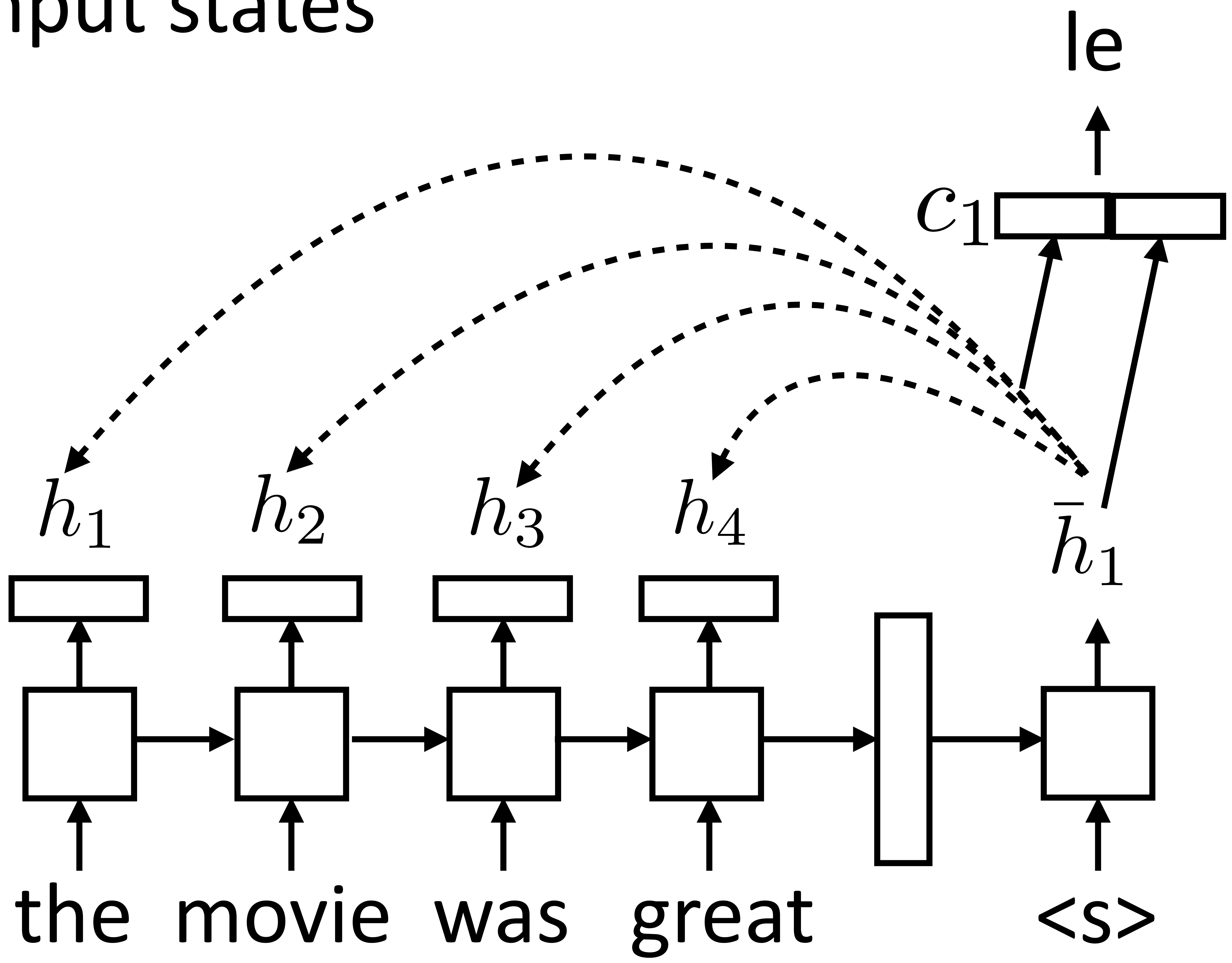

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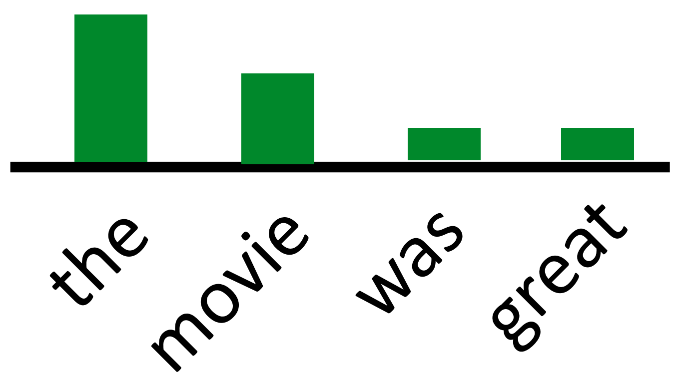

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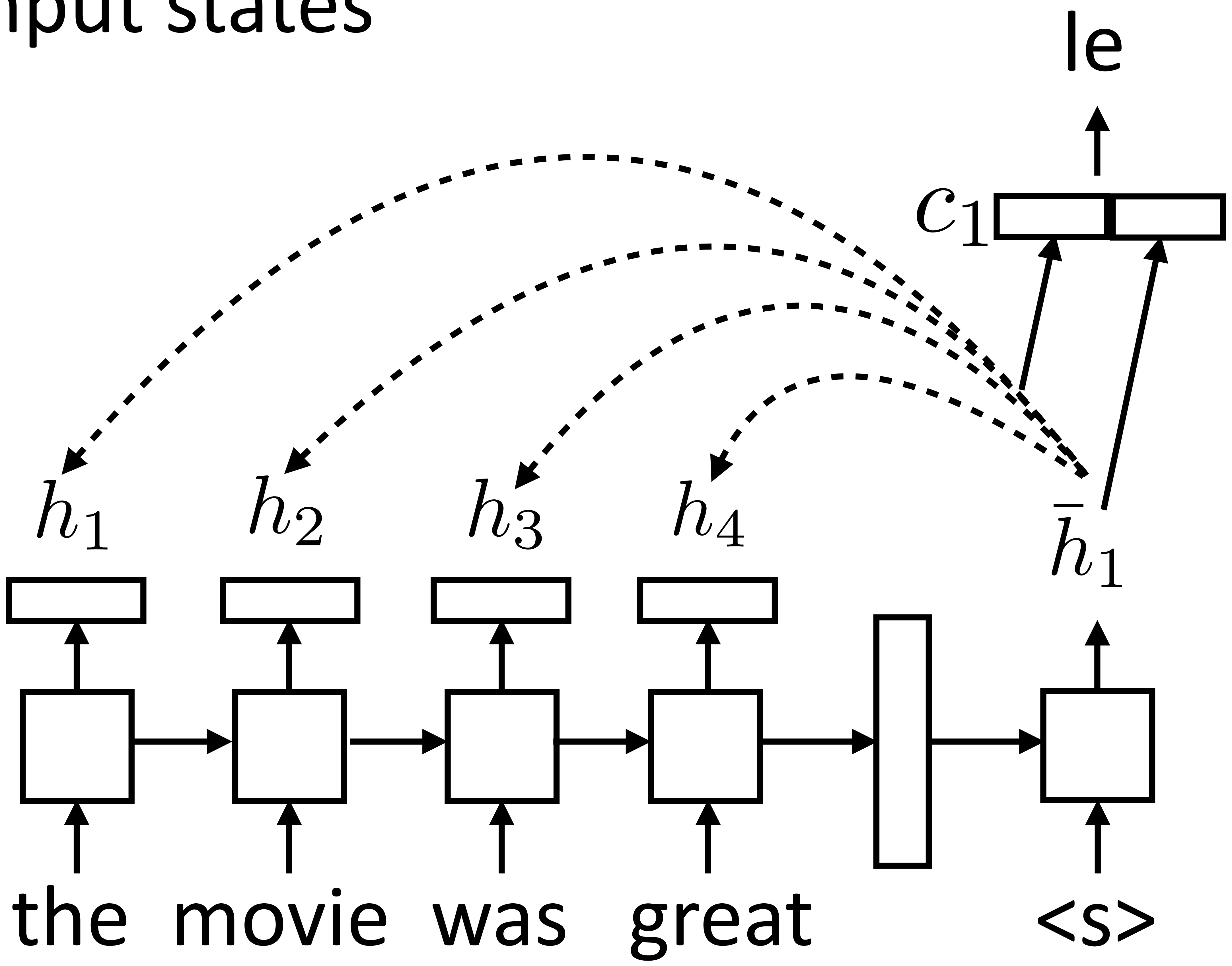

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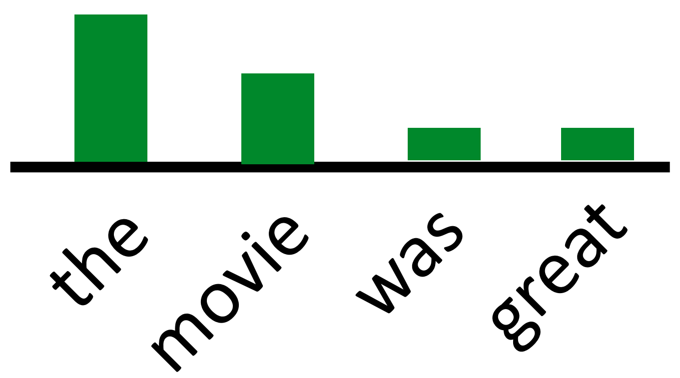

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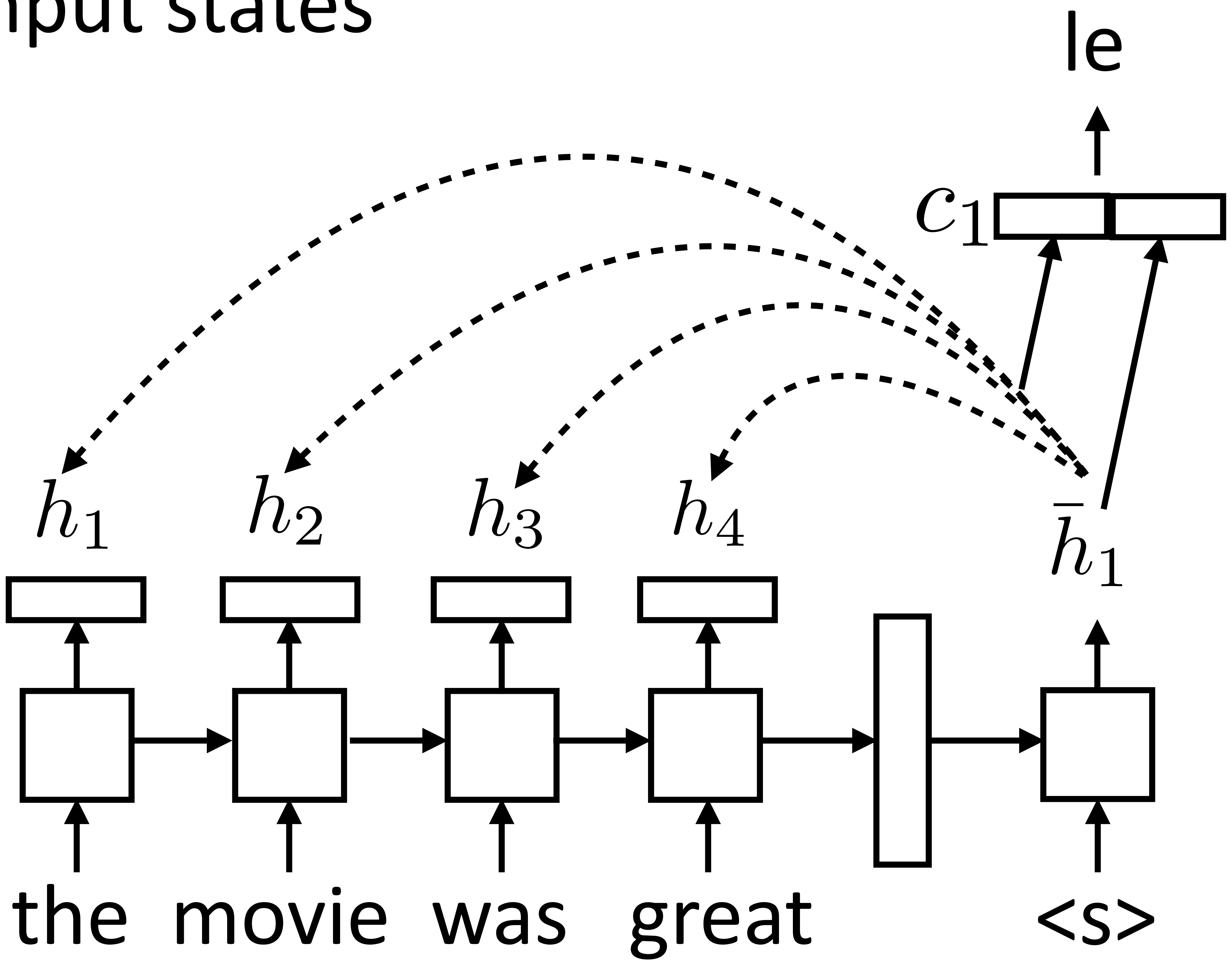

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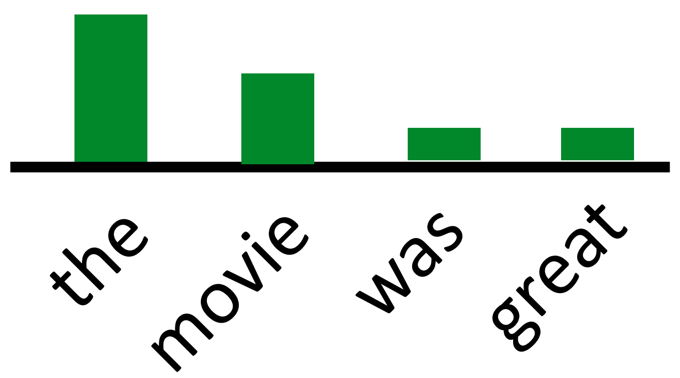

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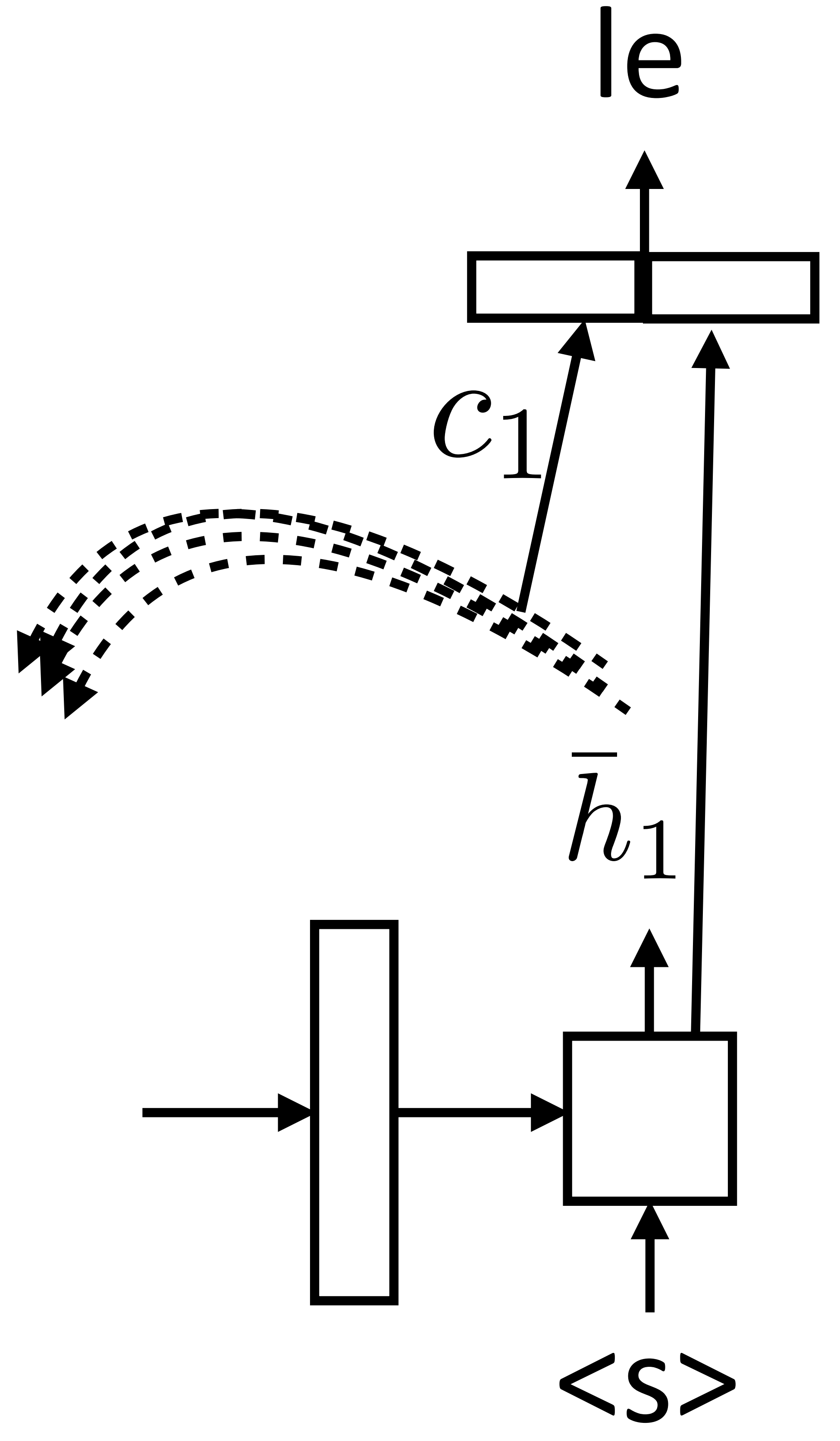

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Luong et al. (2015)

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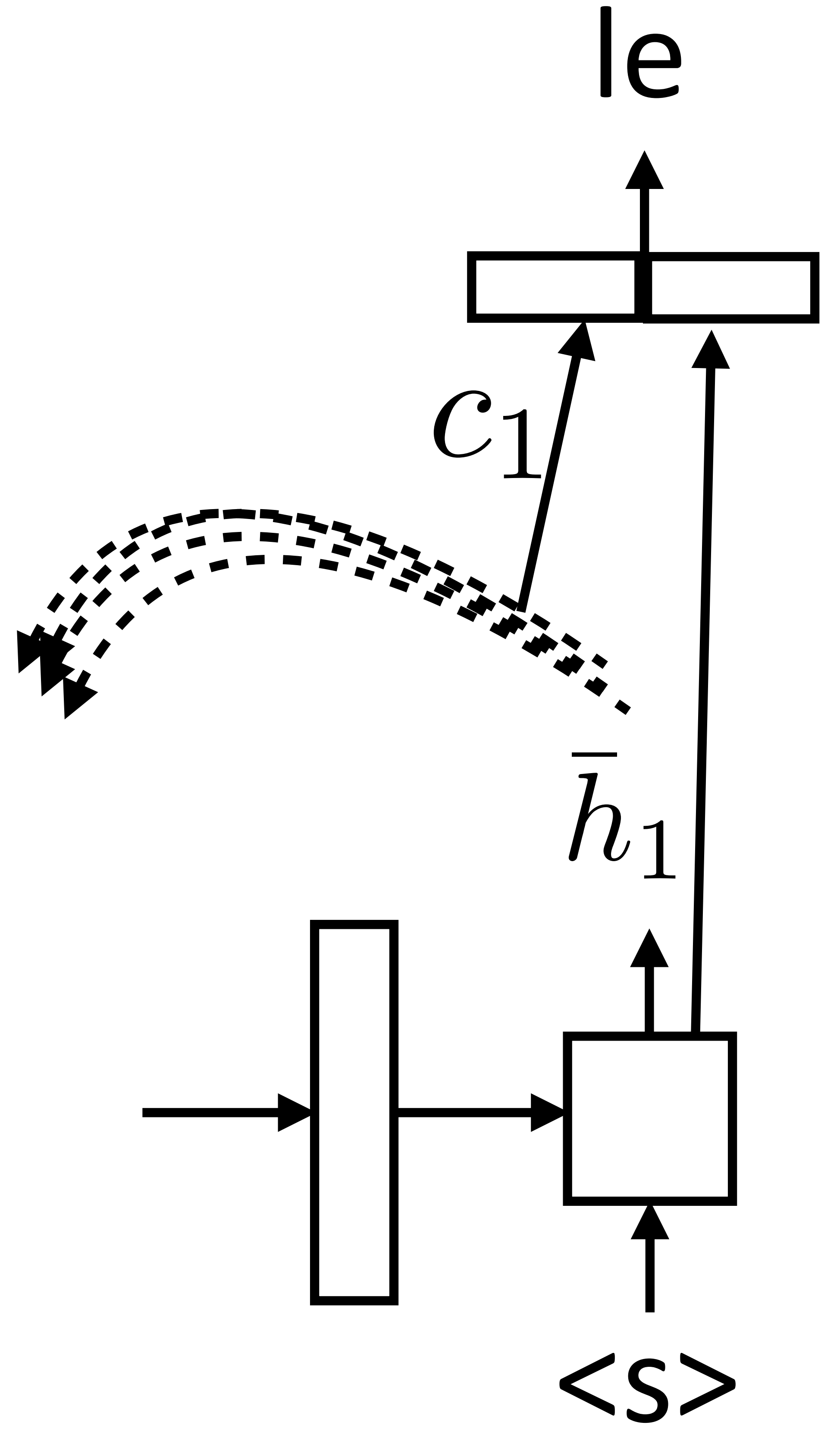

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- Bahdanau+ (2014): additive

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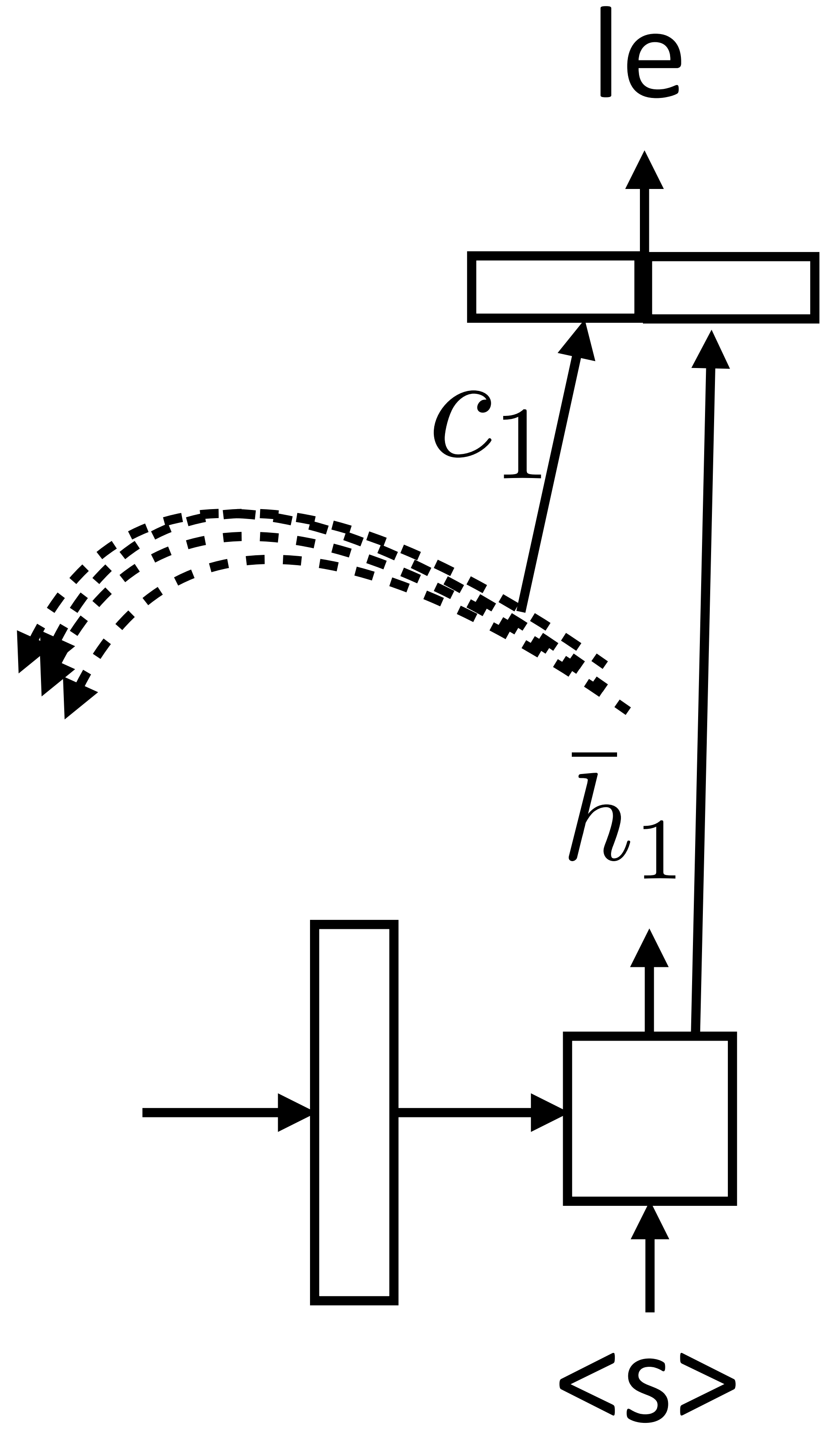

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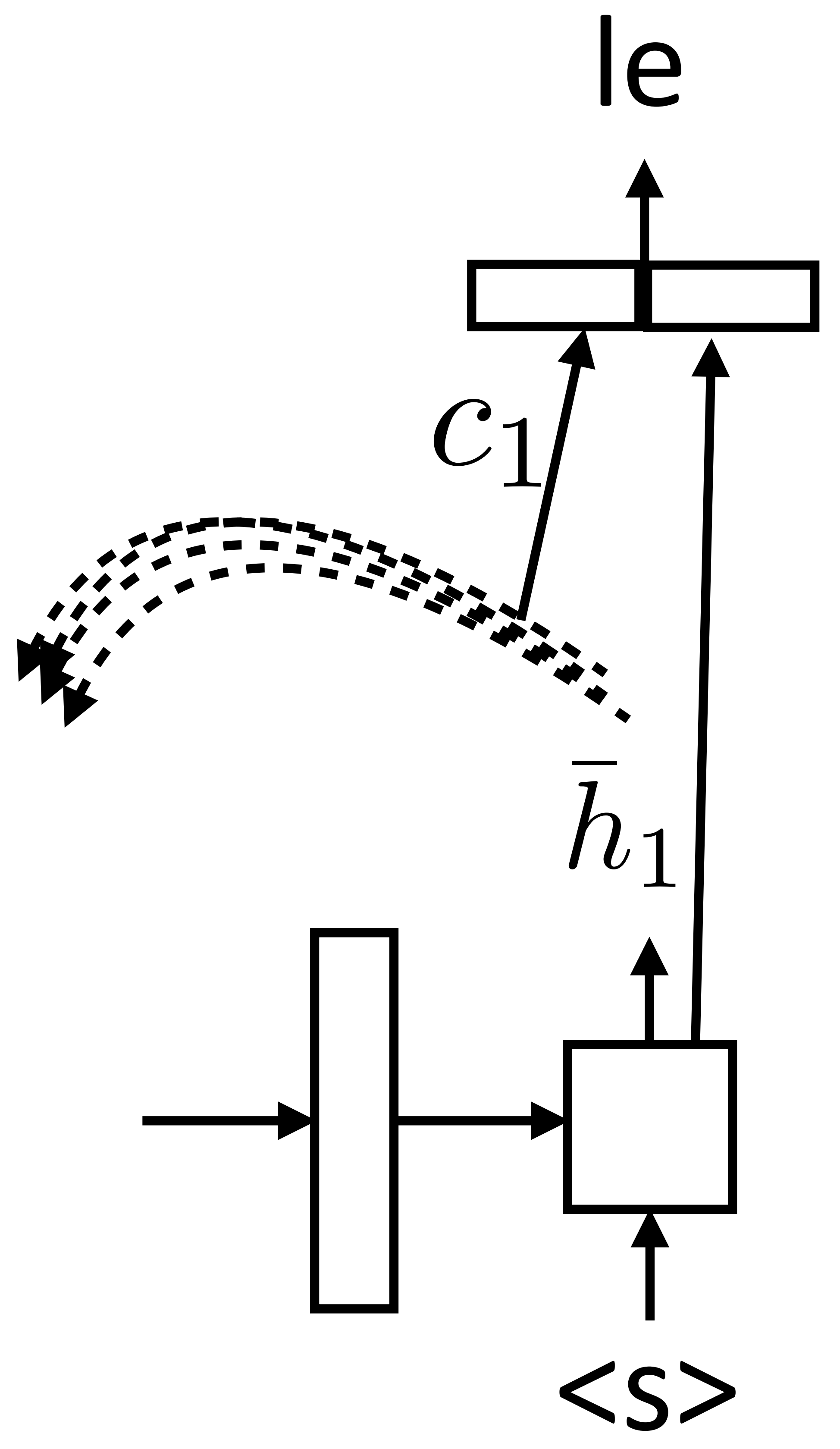

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Luong et al. (2015)

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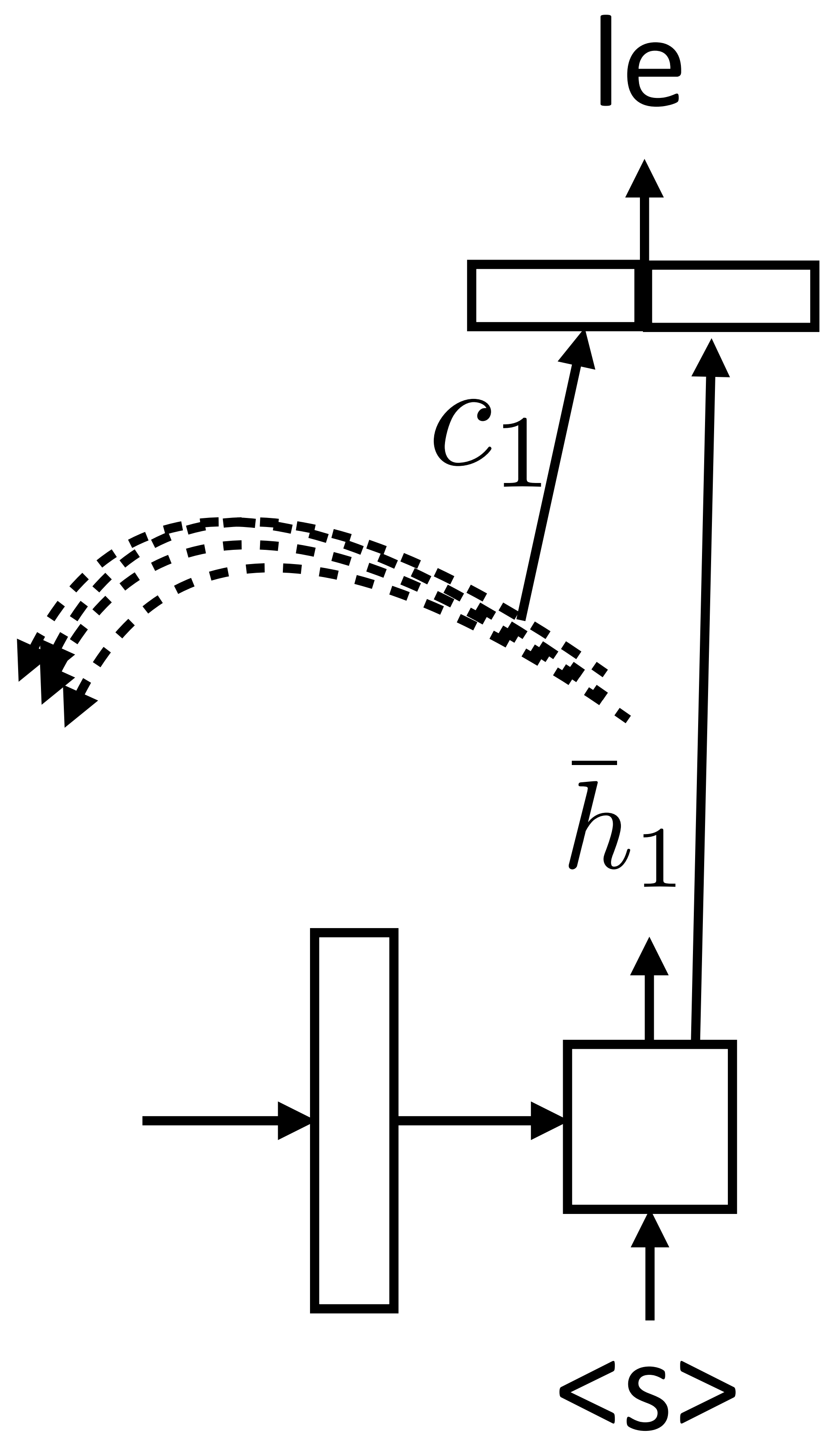

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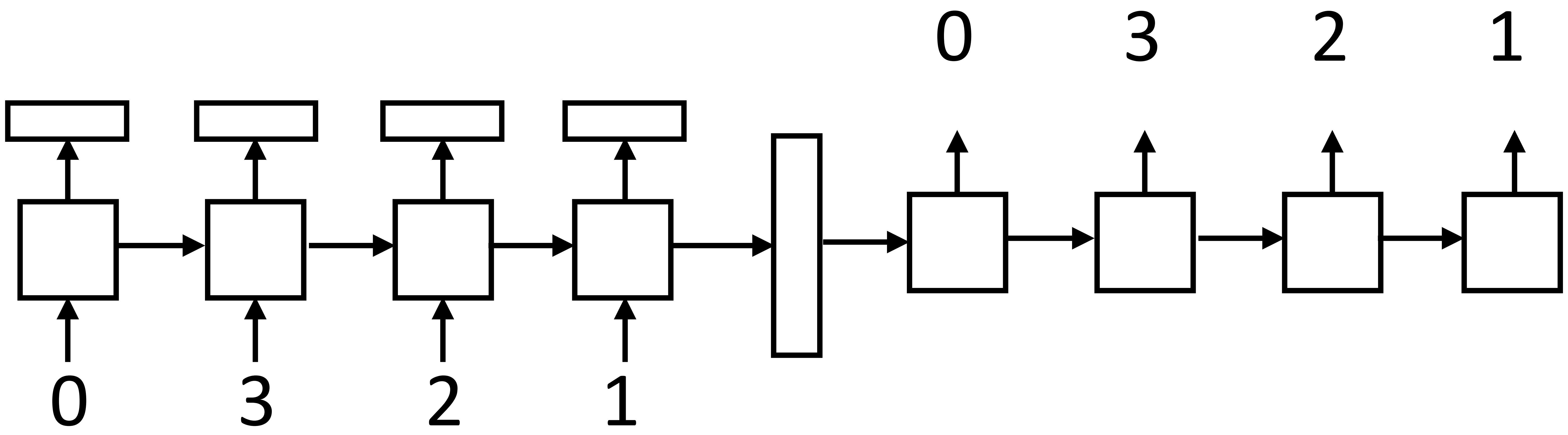
- Note that this all uses outputs of hidden layers

Luong et al. (2015)

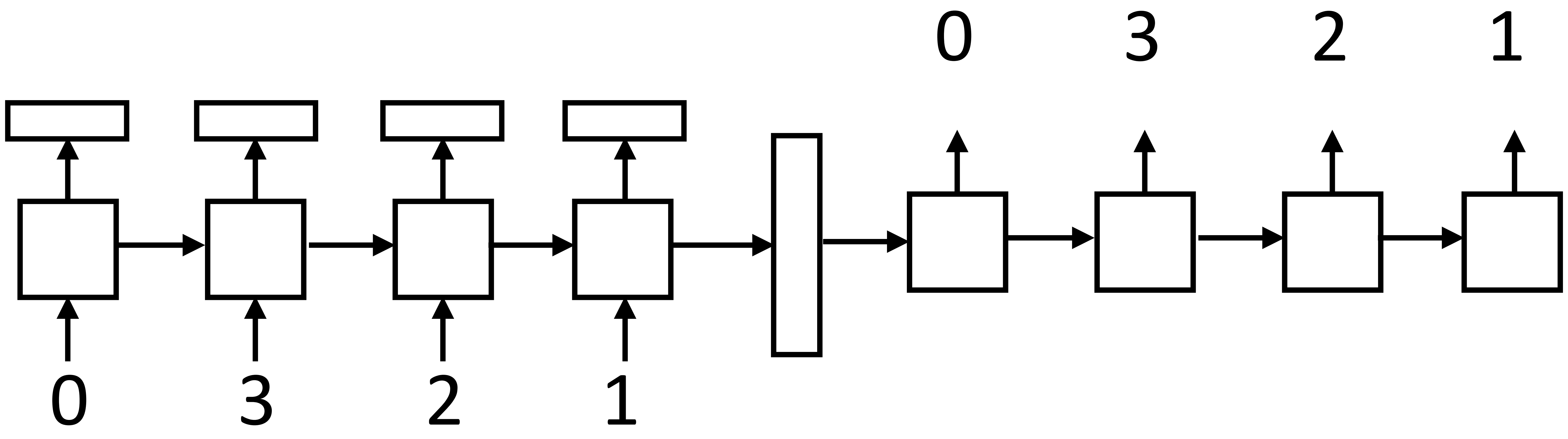
What can attention do?



Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?



Luong et al. (2015)

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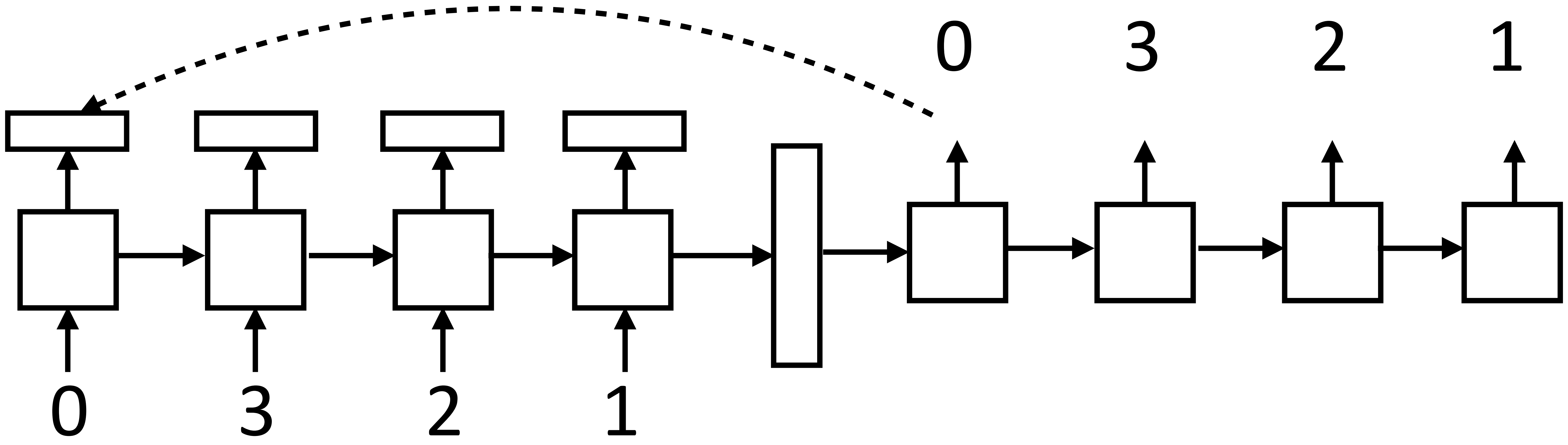

Luong et al. (2015)

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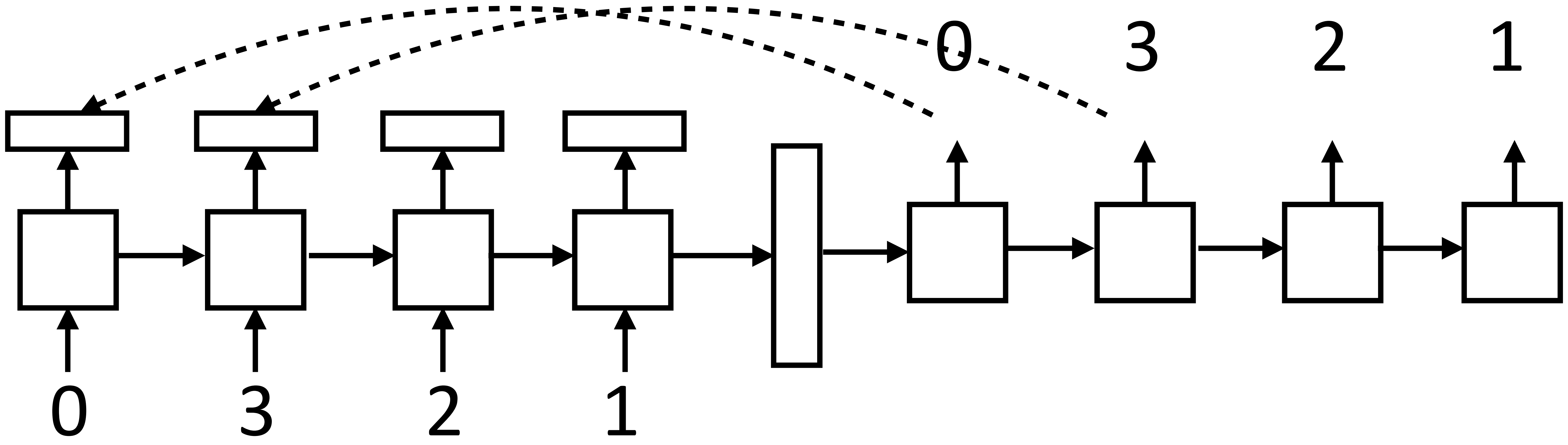
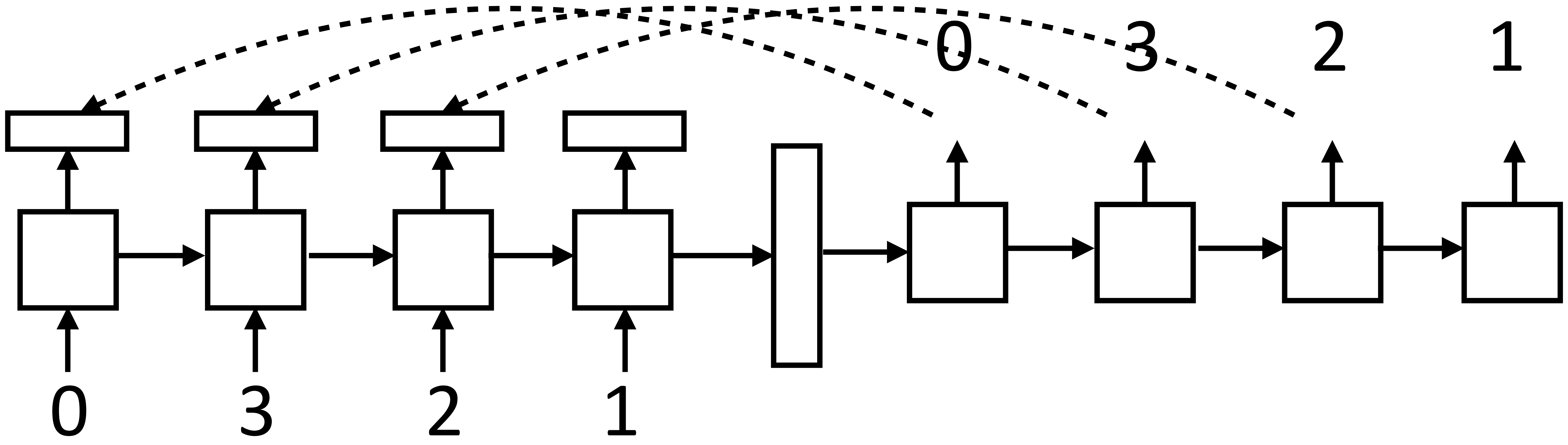


Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?



Luong et al. (2015)

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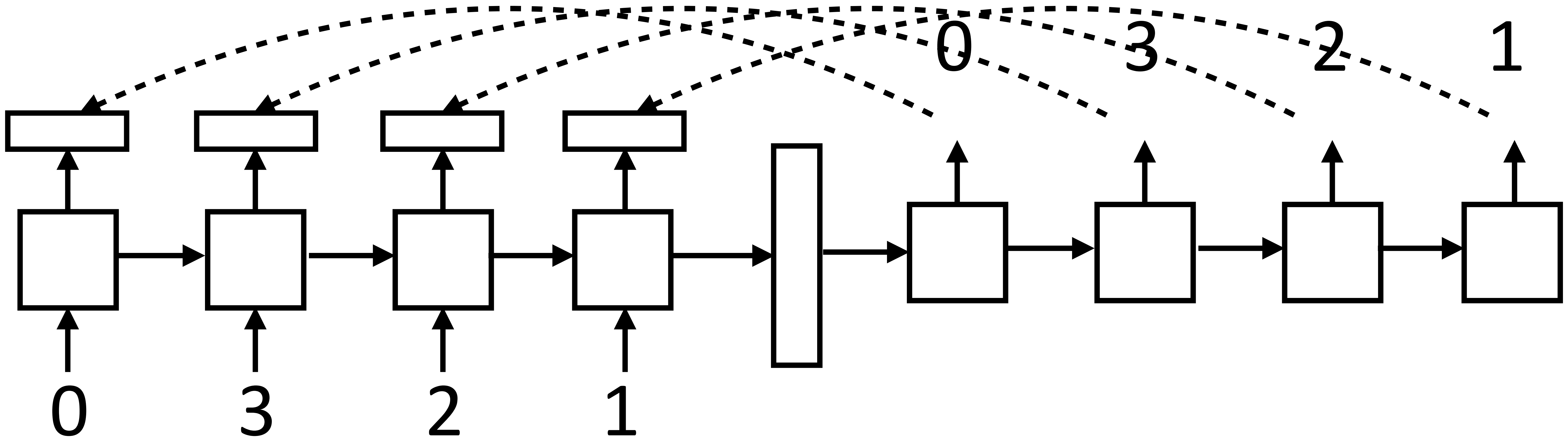

Luong et al. (2015)

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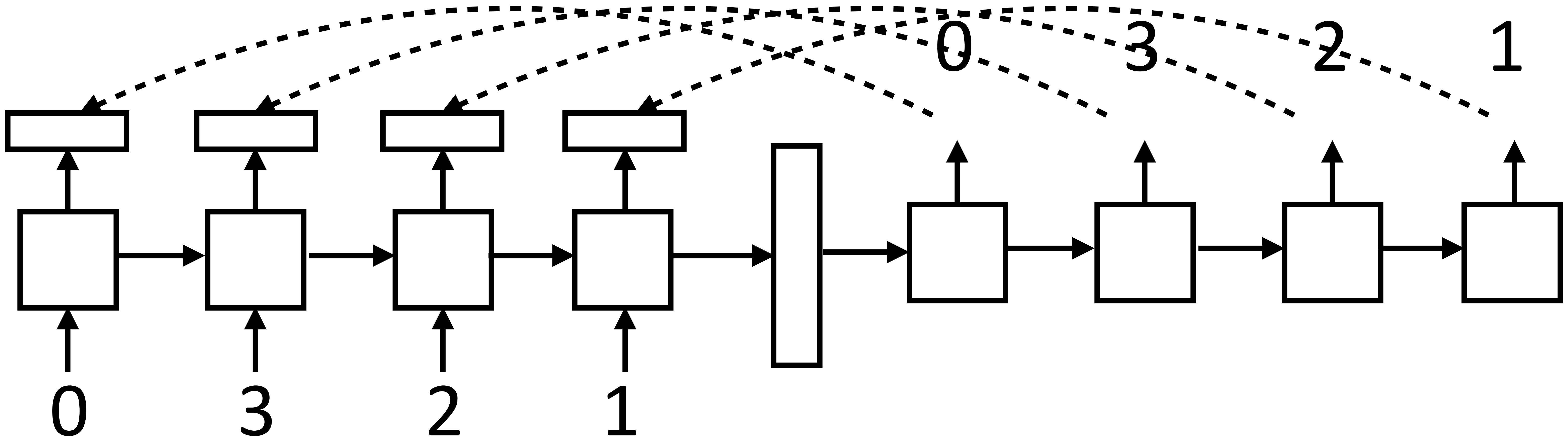

- LSTM can learn to count with the right weight matrix

Luong et al. (2015)

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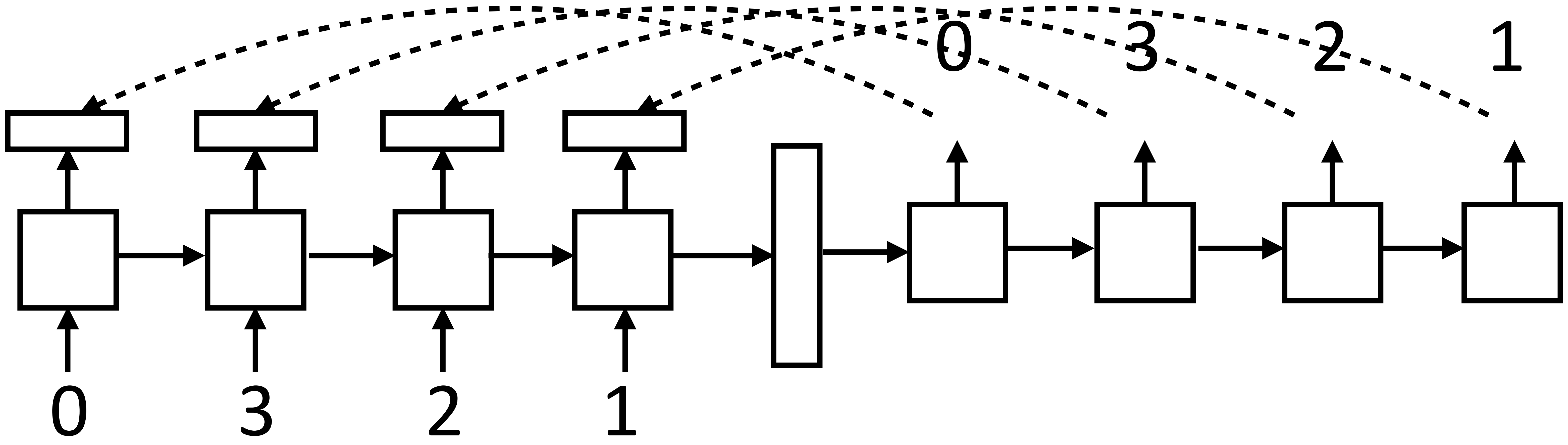
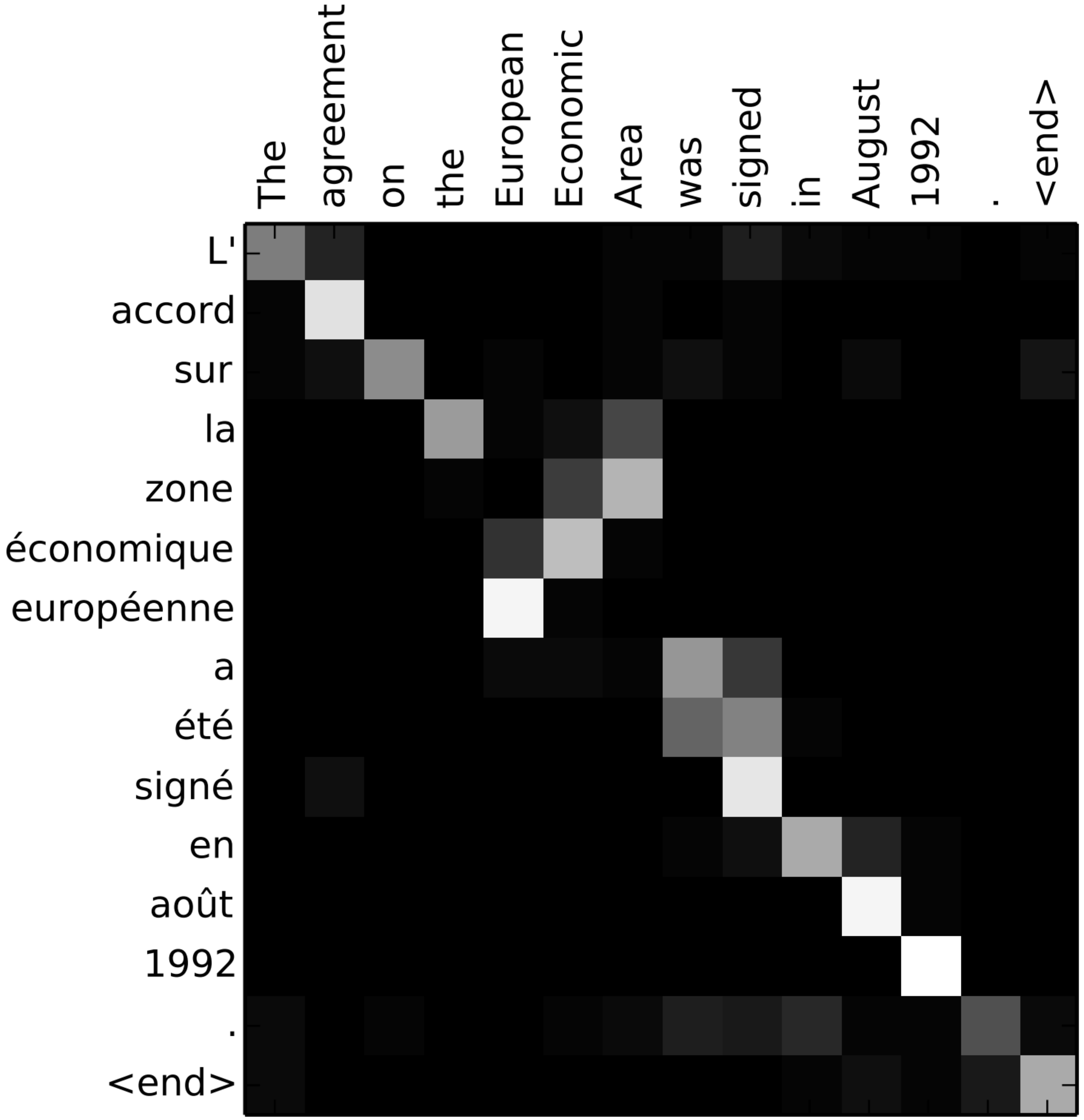


- LSTM can learn to count with the right weight matrix

- This is effectively position-based addressing

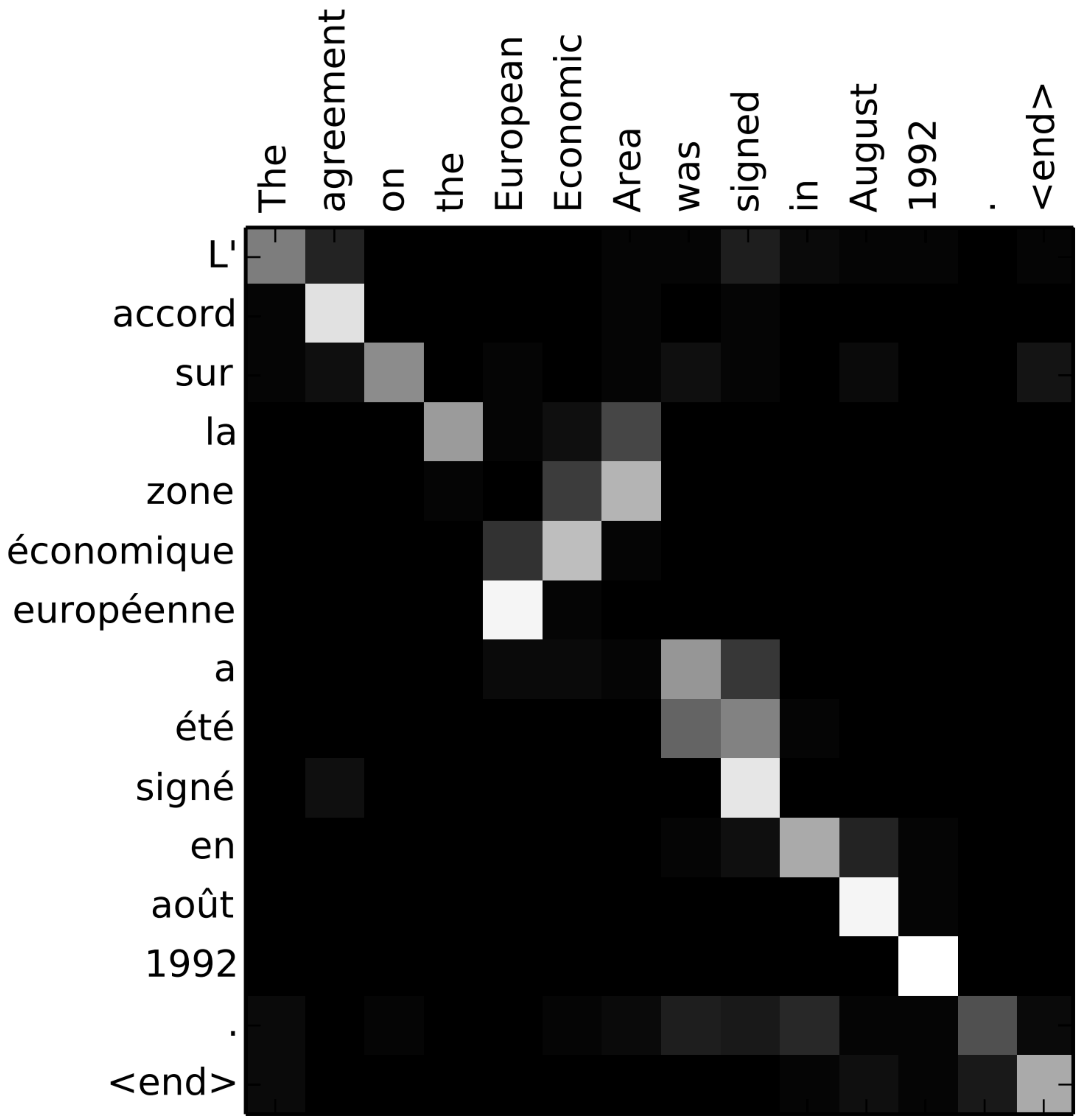
Luong et al. (2015)

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

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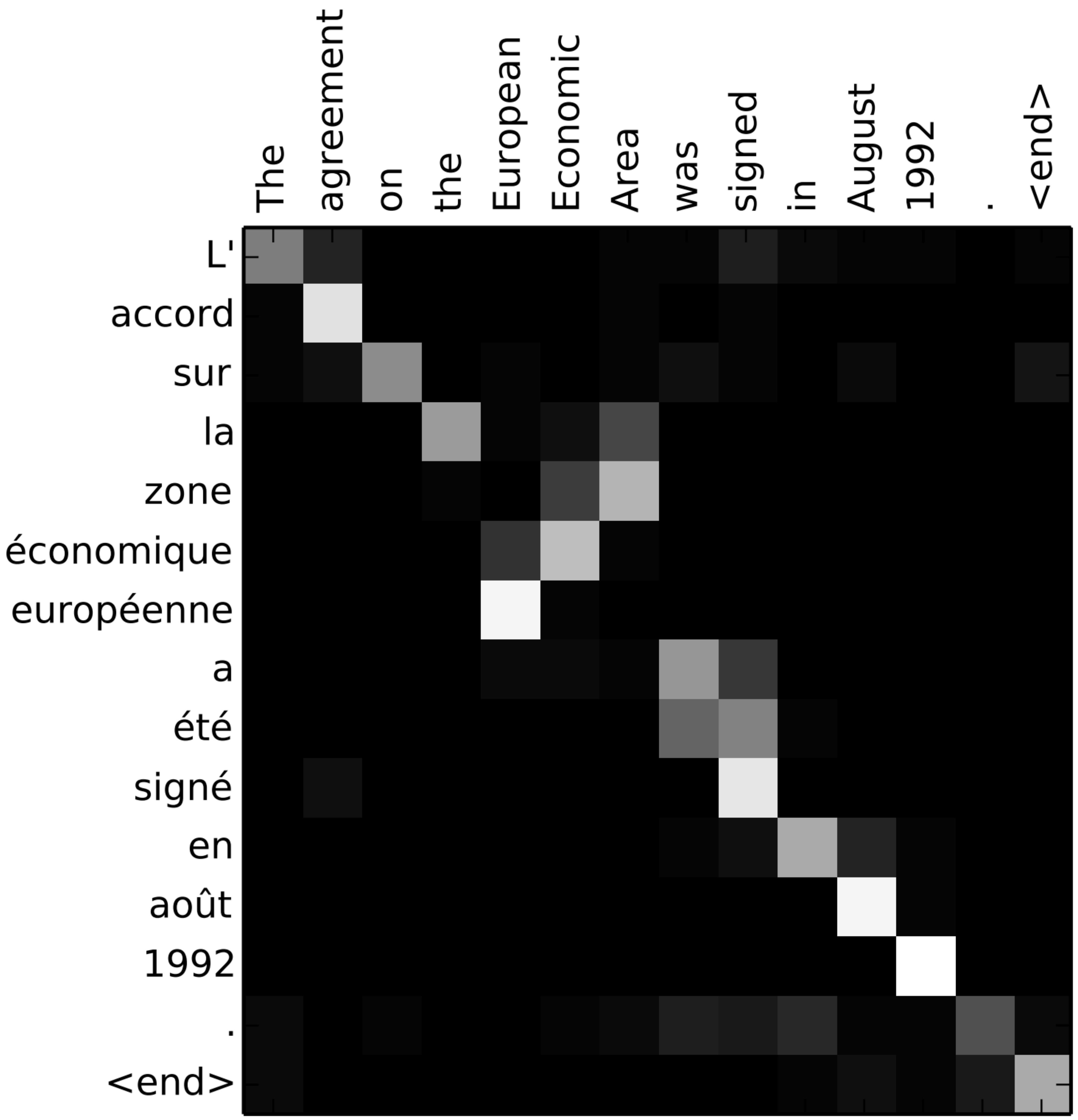
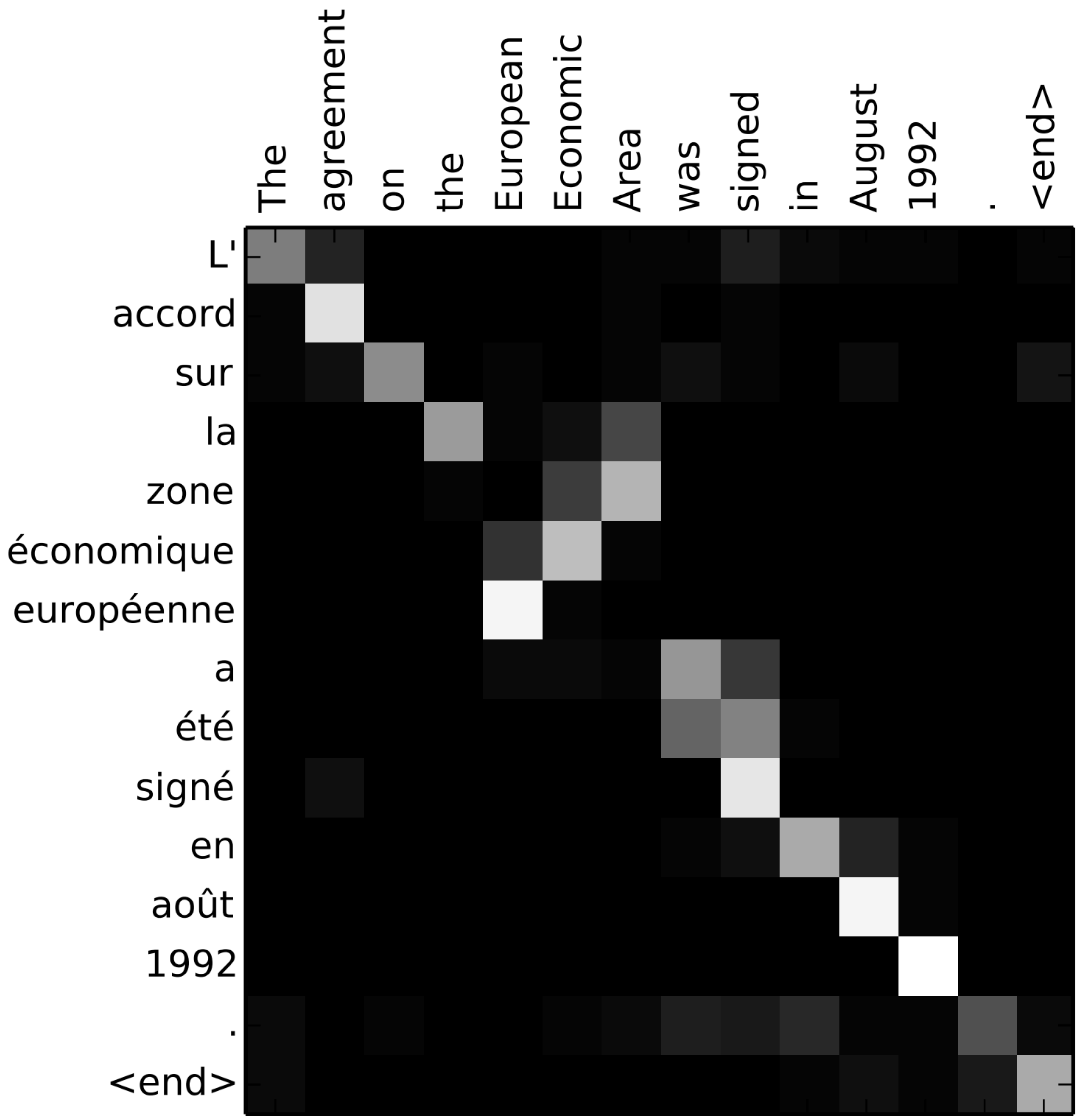
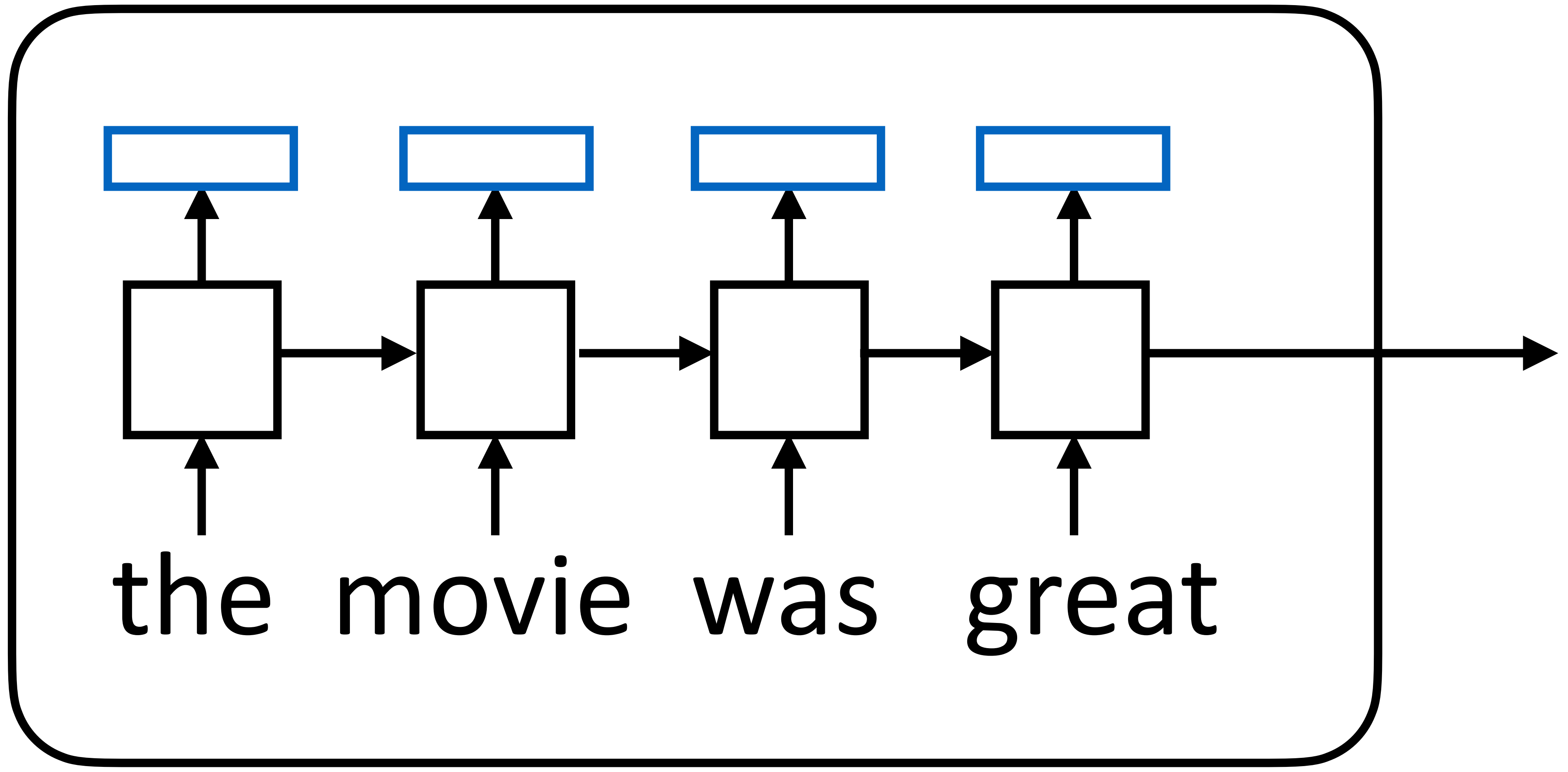


Attention

- 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



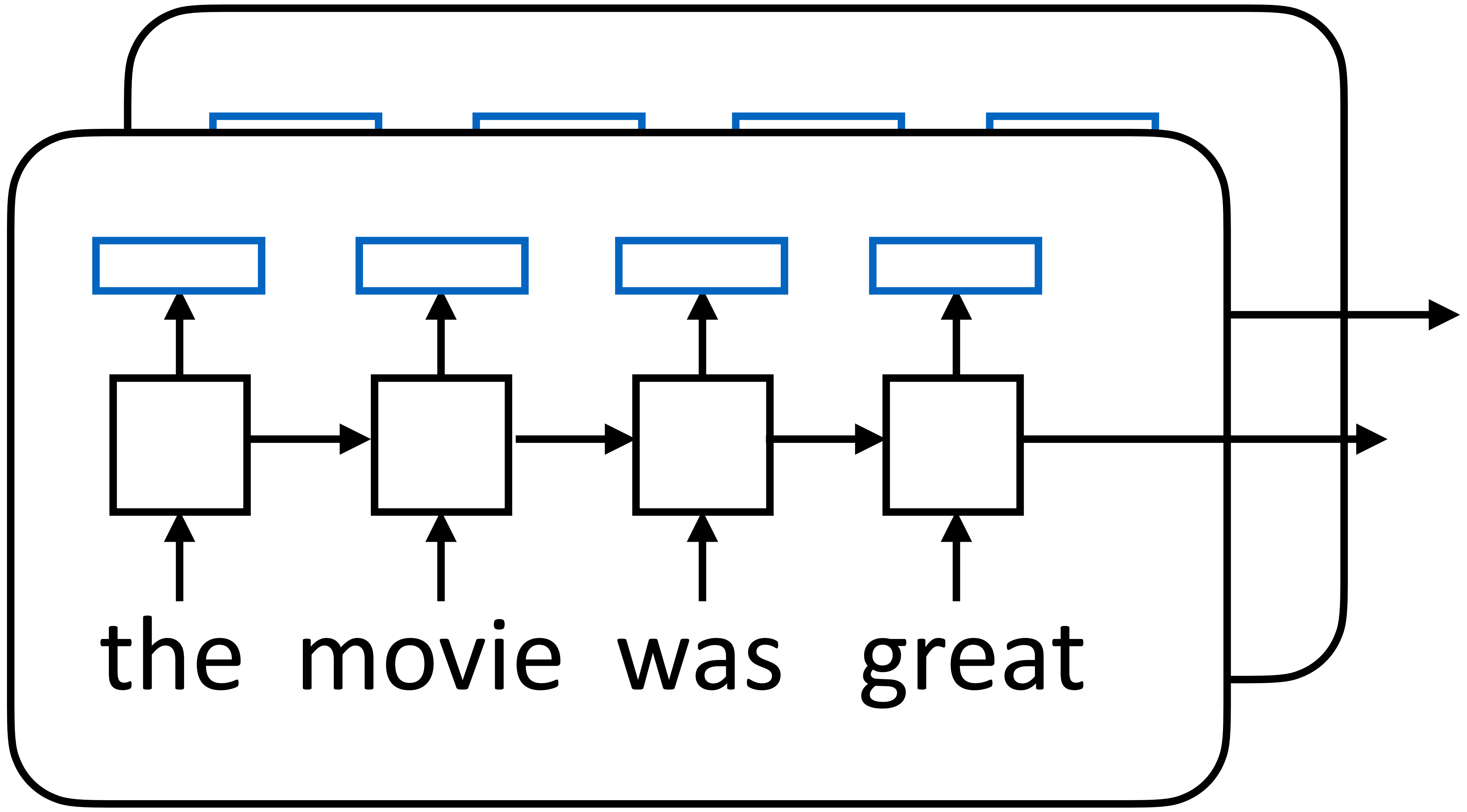
Batching Attention



Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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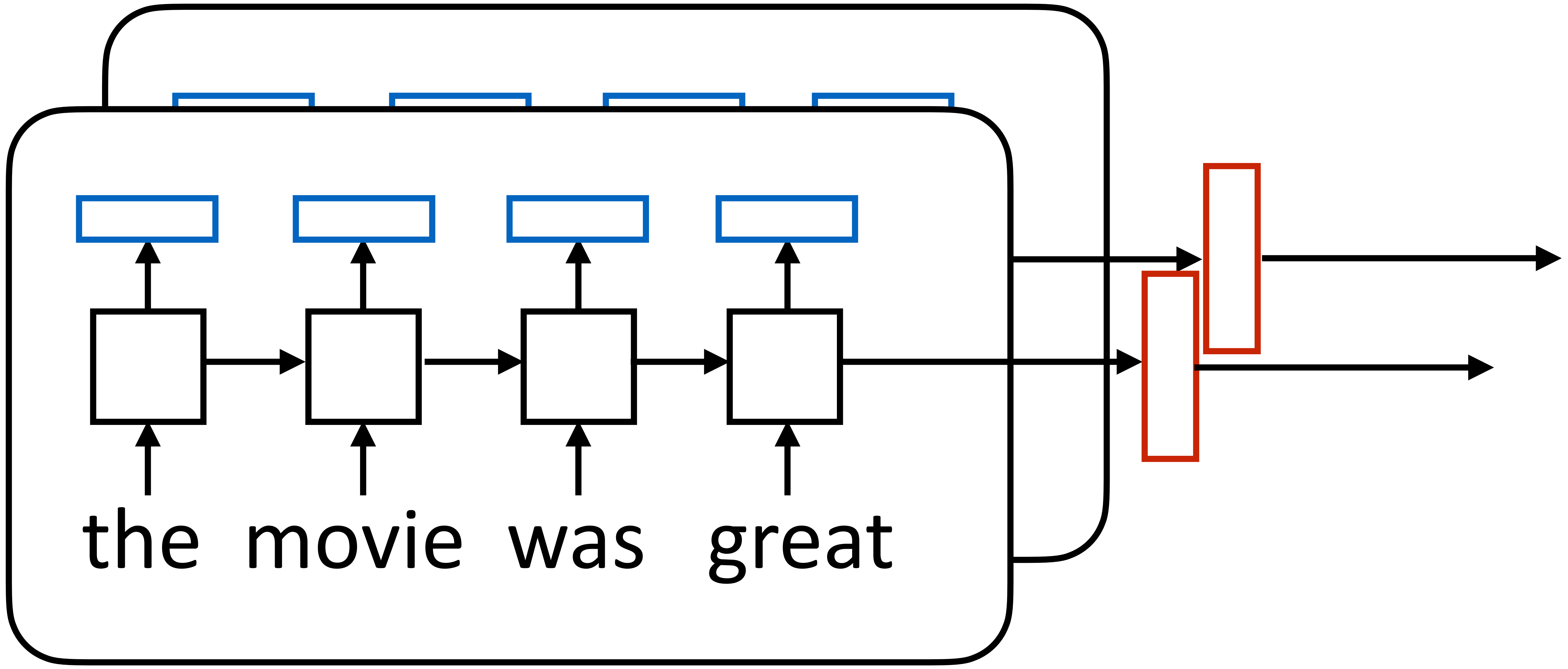

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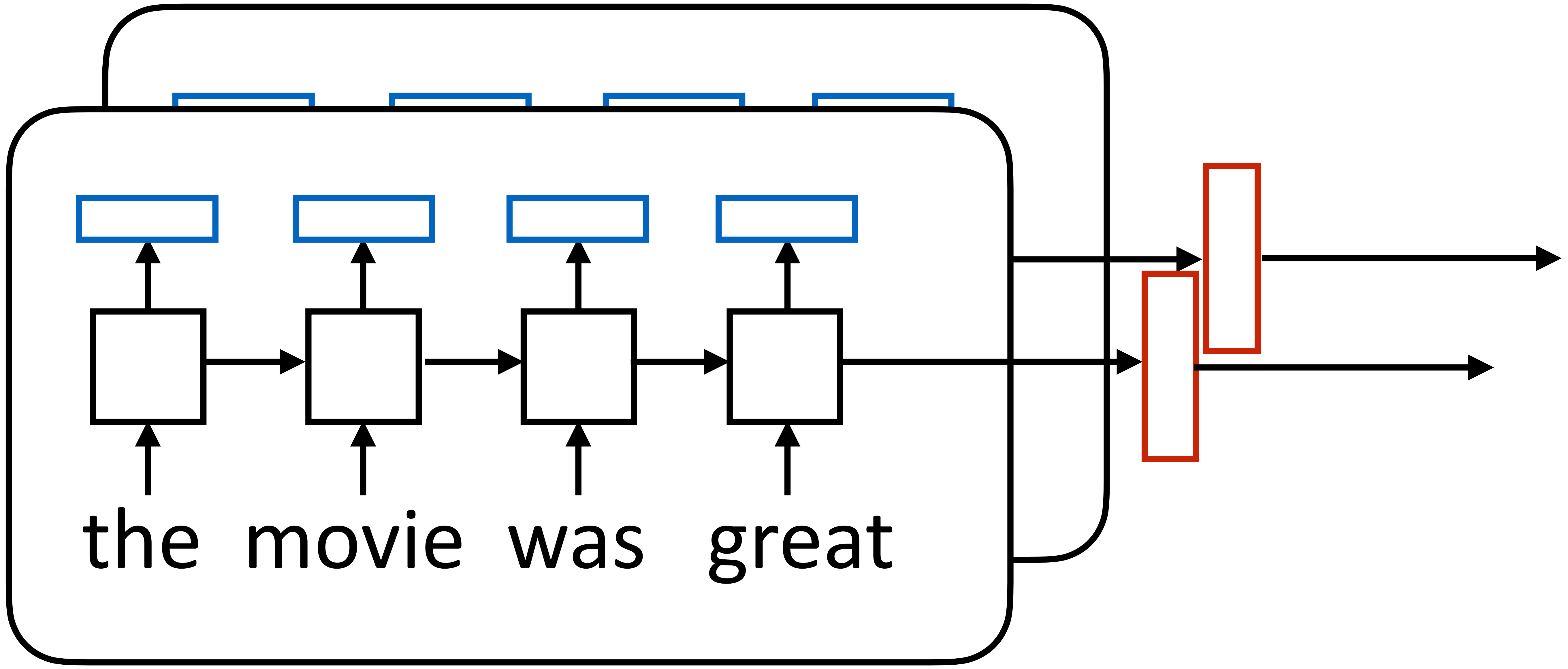

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batch size x hidden size

Luong et al. (2015)

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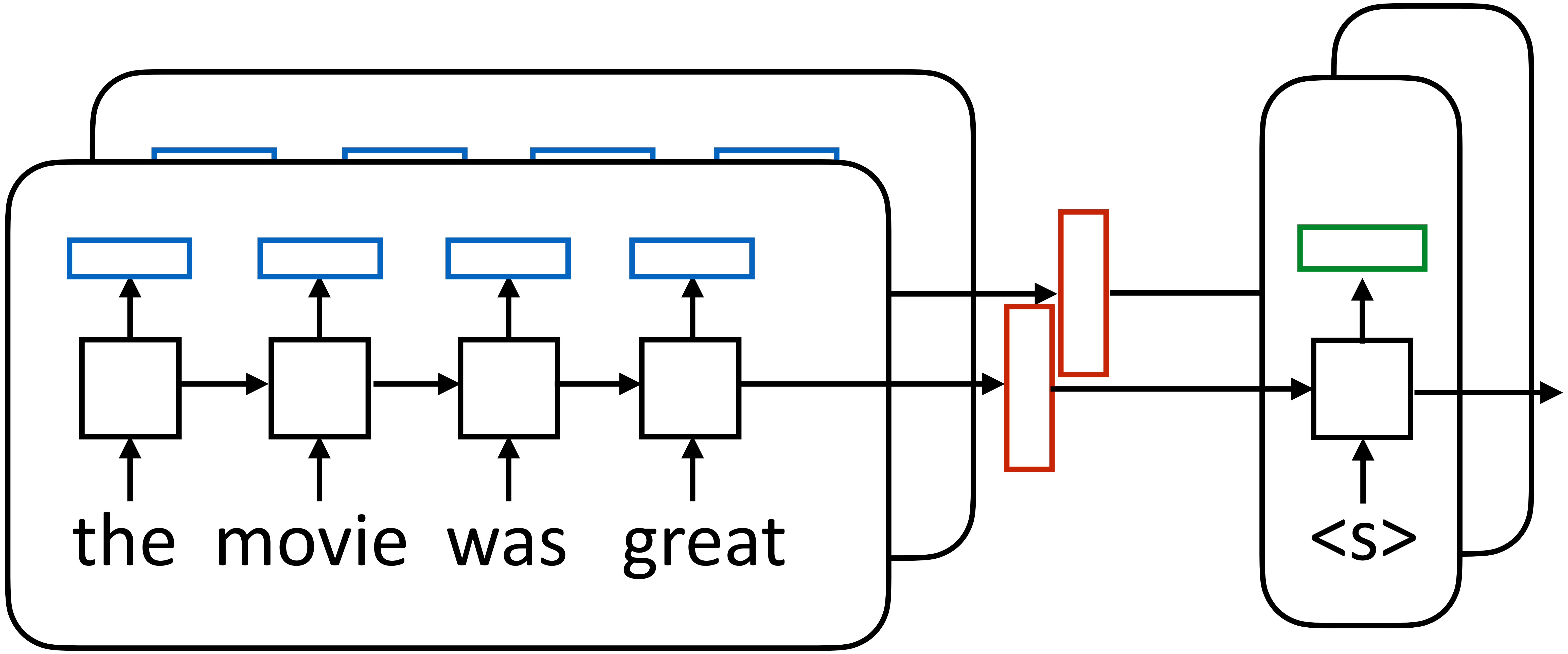

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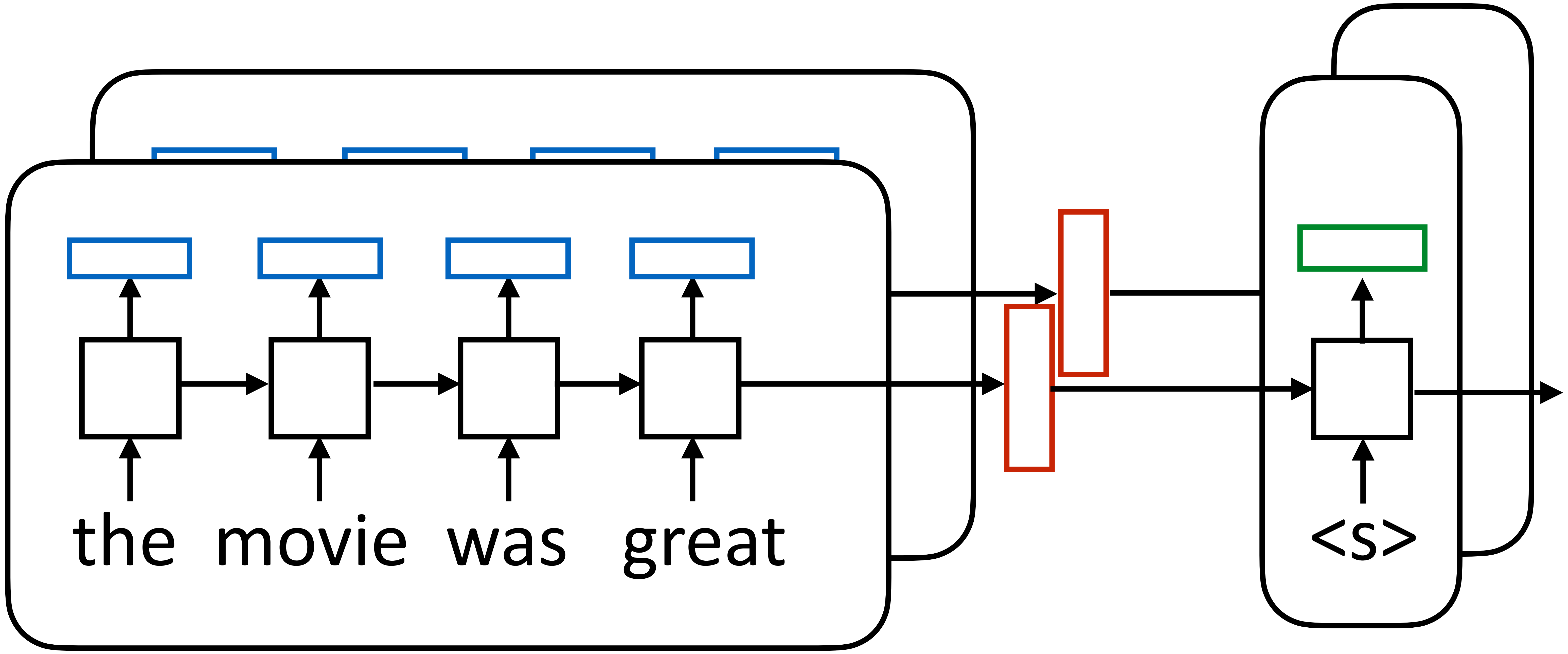

hidden state: batch size x hidden size

sentence outputs:
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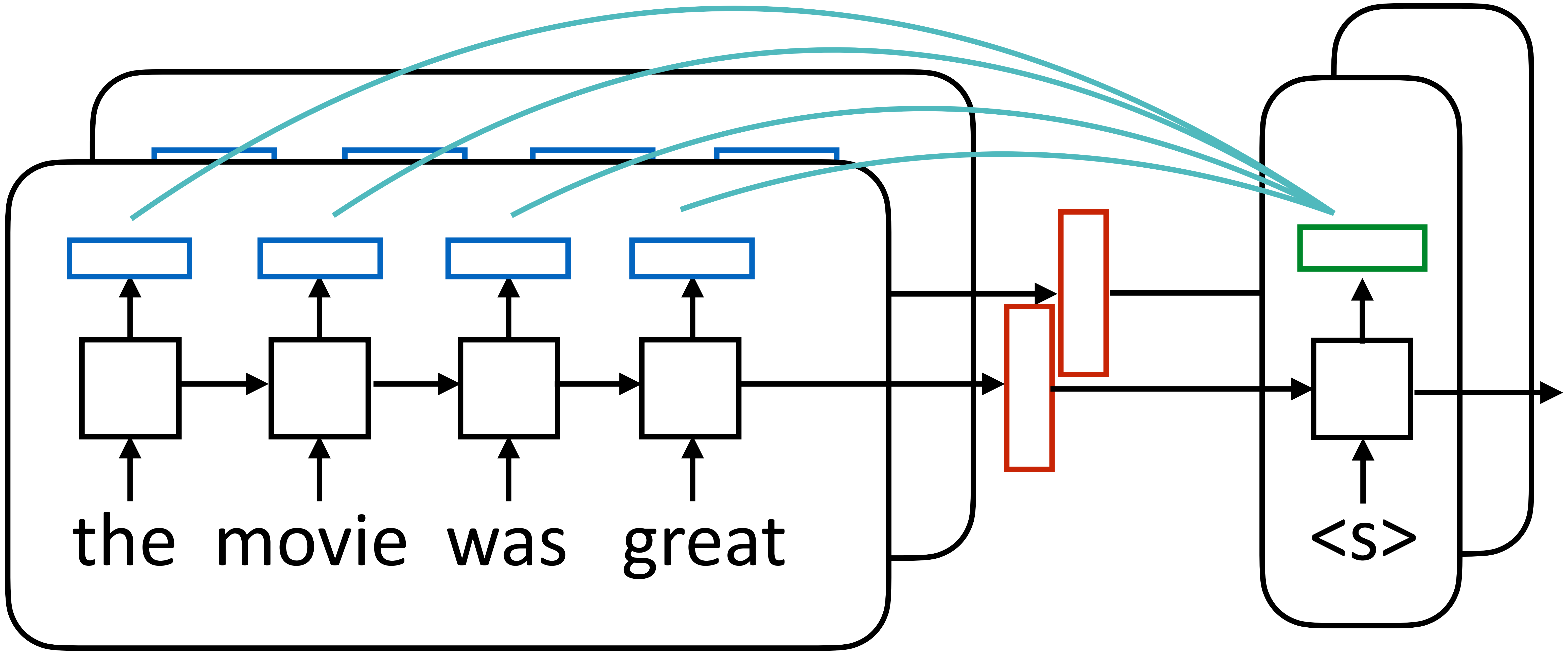
Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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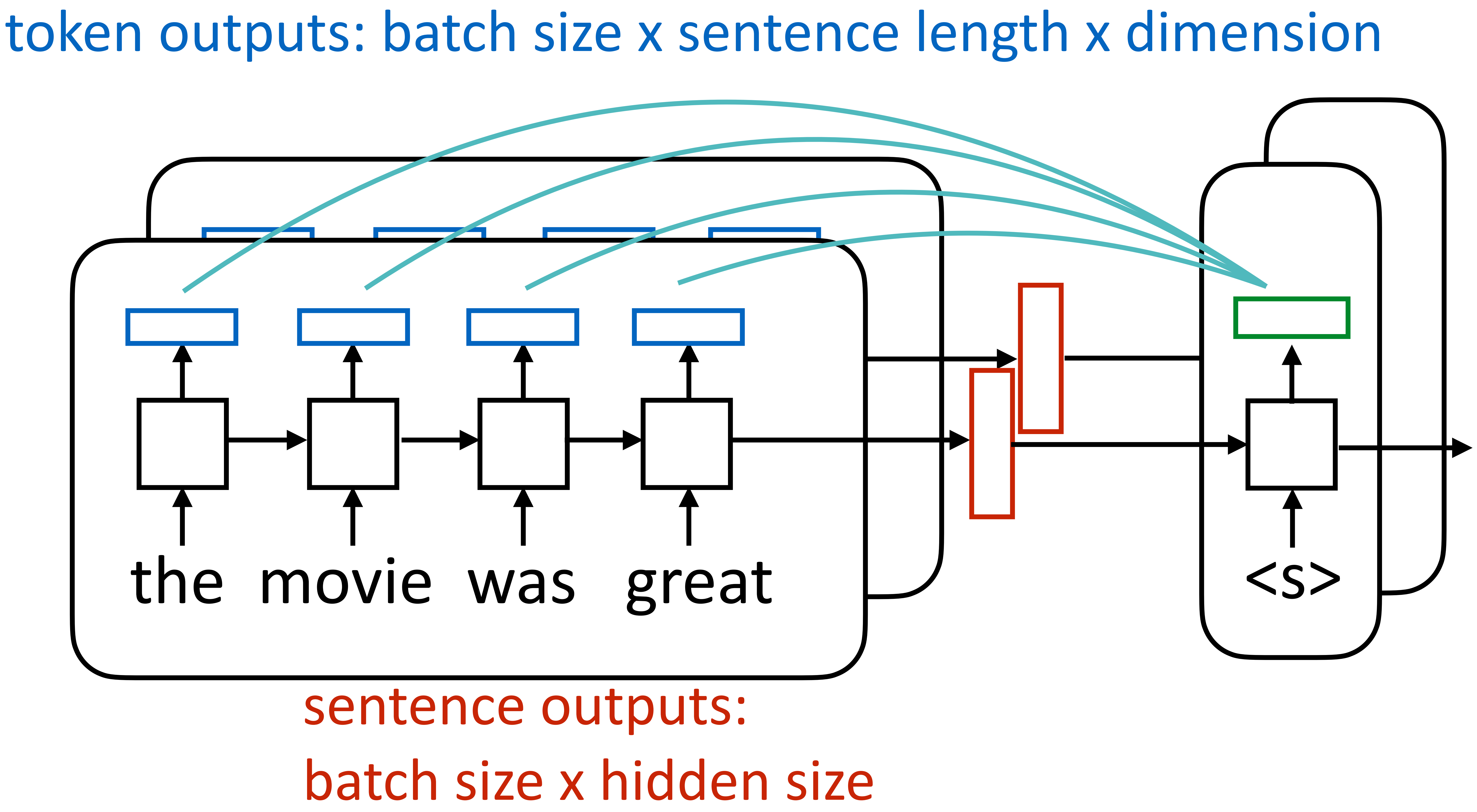

$$e_{ij} = f(\bar{h}_i, h_j)$$

Luong et al. (2015)

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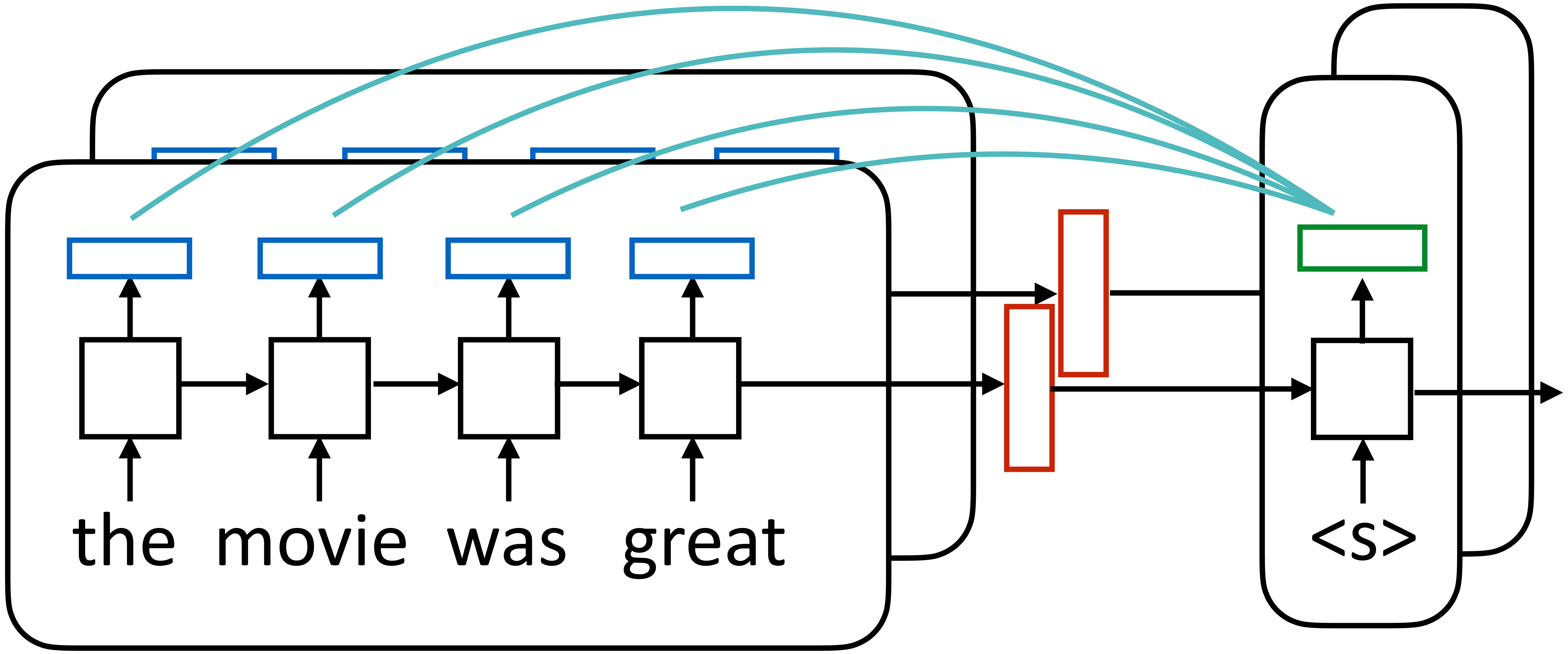

hidden state: batch size x hidden size

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

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

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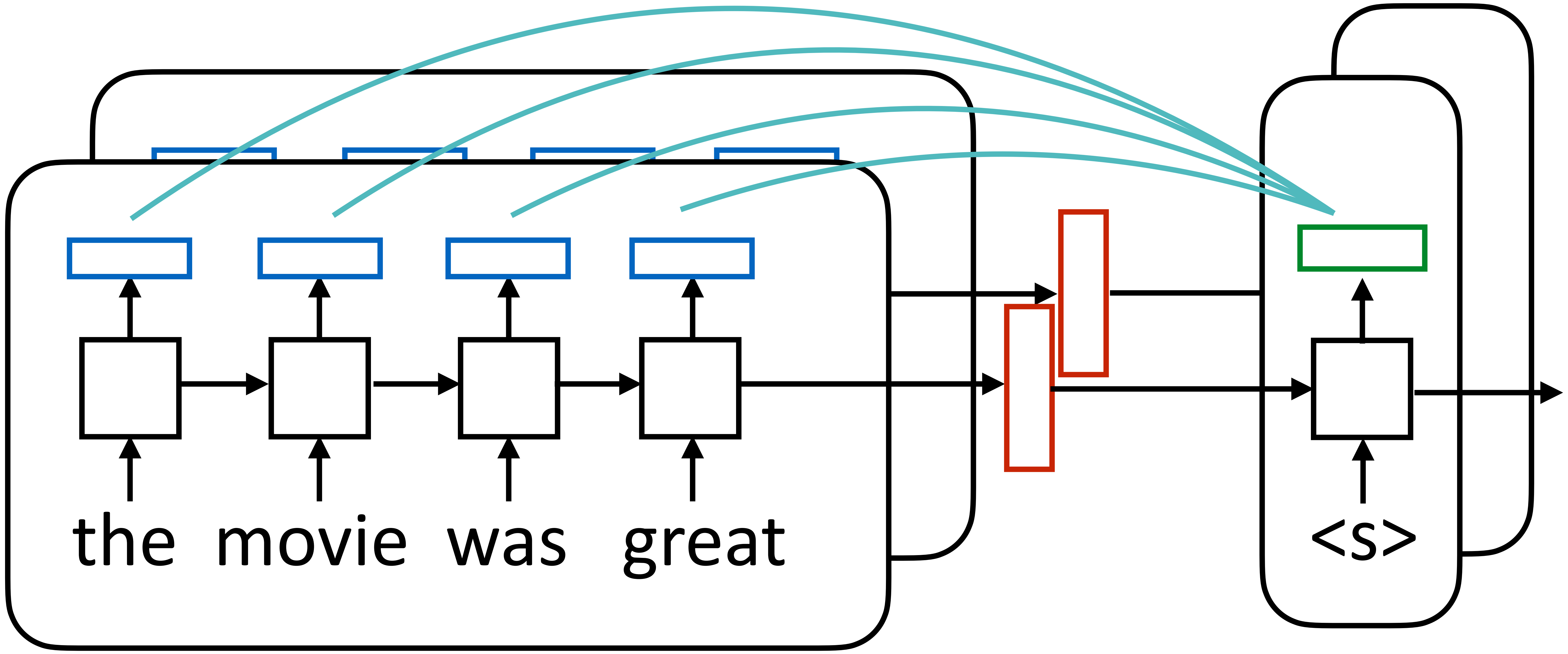
Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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attention scores = batch size x sentence length

Luong et al. (2015)

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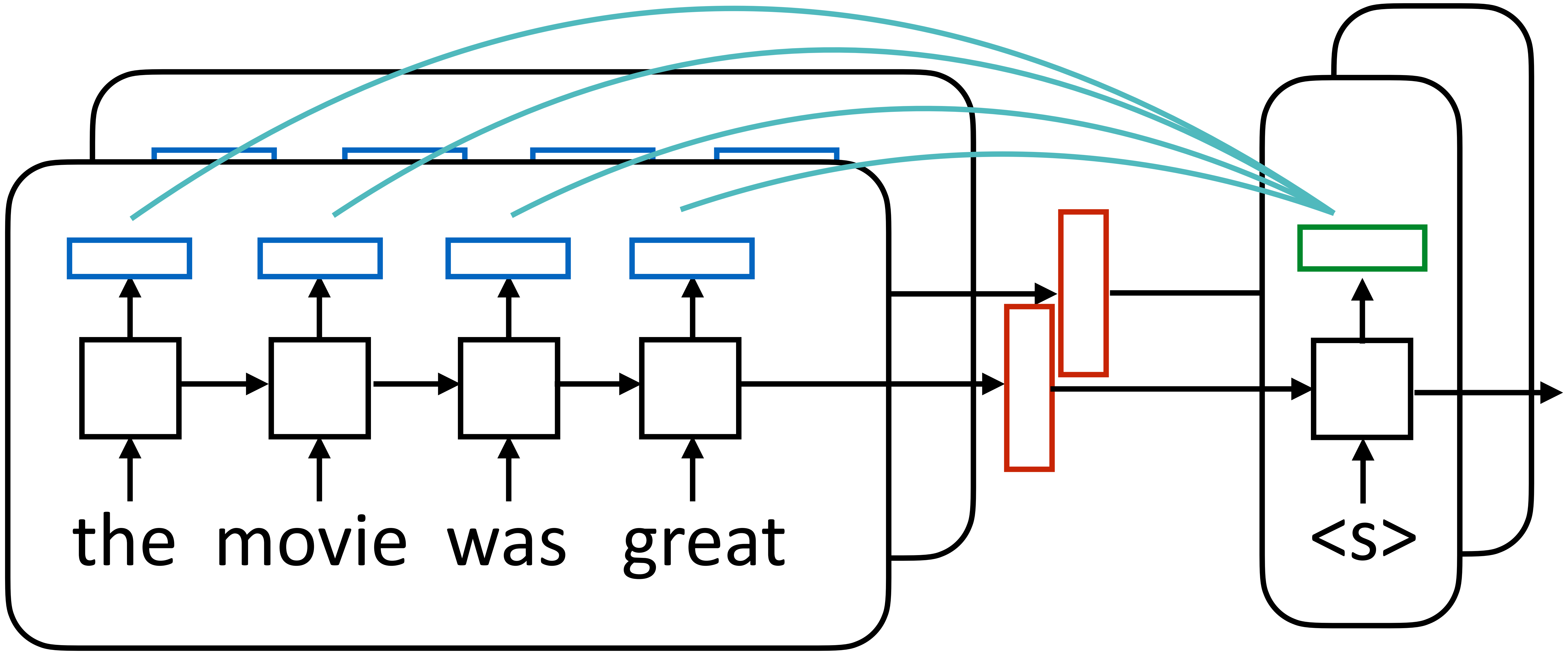

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c = batch size x hidden size

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

Luong et al. (2015)

Batching Attention

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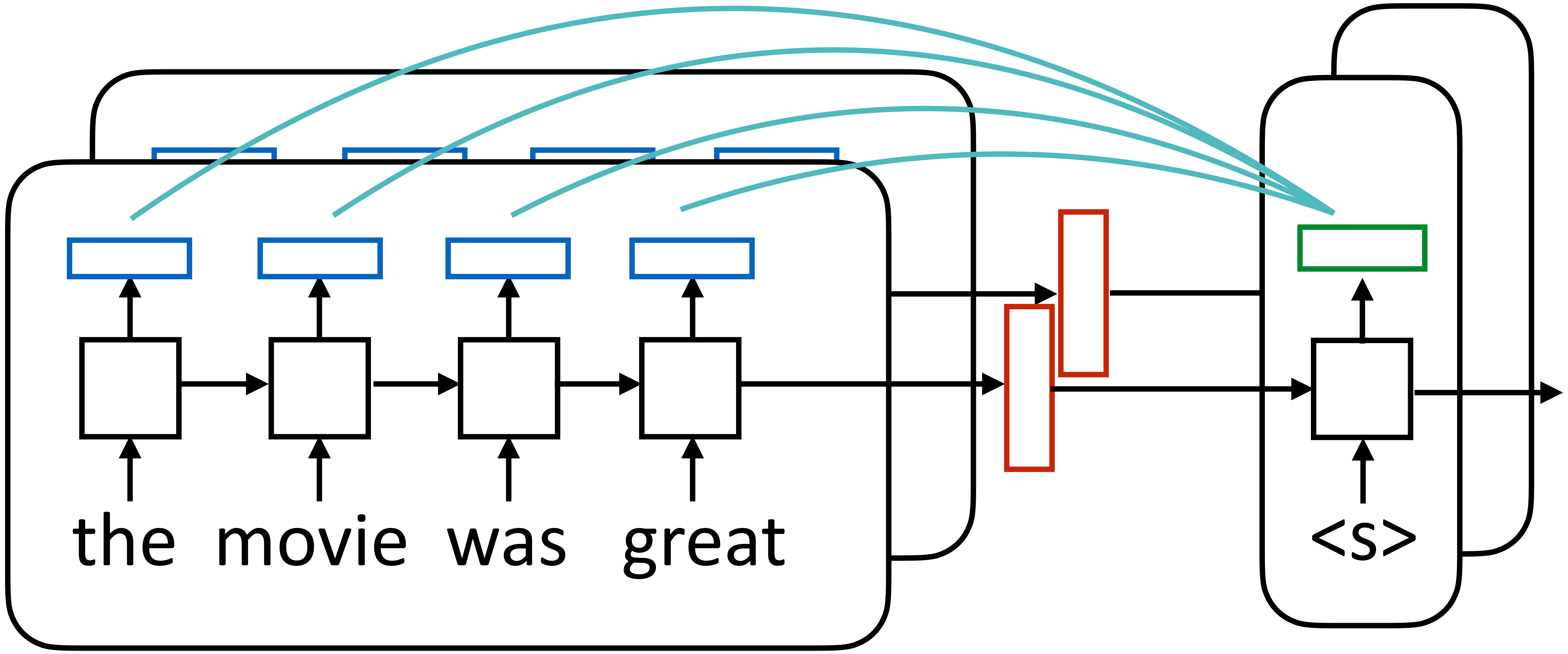

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$$c_i = \sum_j \alpha_{ij} h_j$$

- 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)

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- 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)

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1

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

Unknown Words

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

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

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

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from attention

from RNN hidden state

- Still can only generate from the vocabulary

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

Copying

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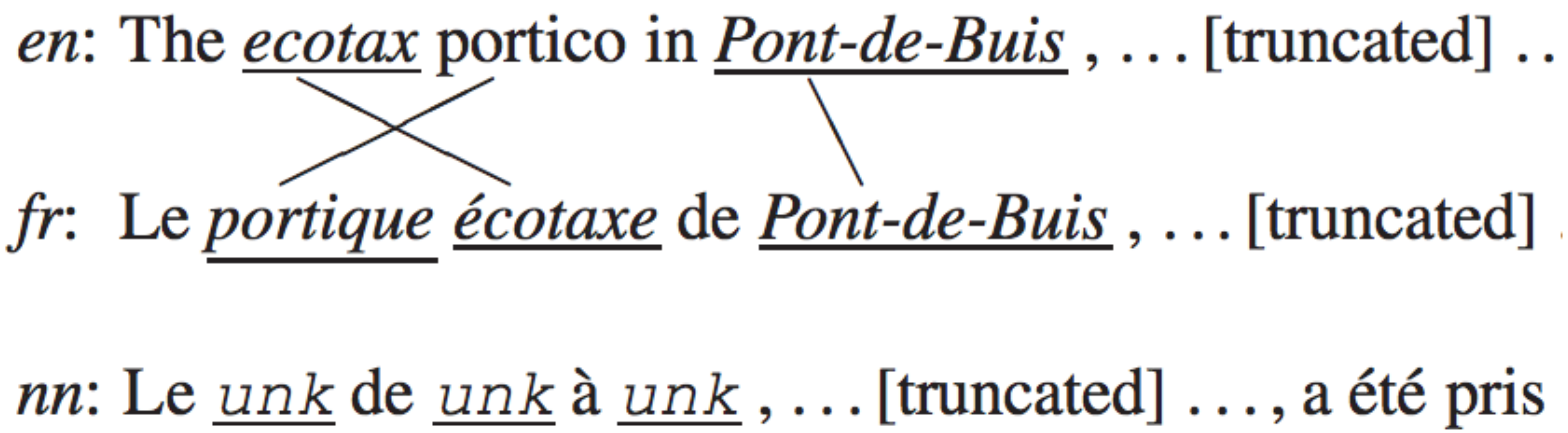
- Vocabulary contains "normal" vocab as well as words in input. Normalizes over both of these:

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

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

Copying

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the
a
…
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Pont-de-Buis
ecotax

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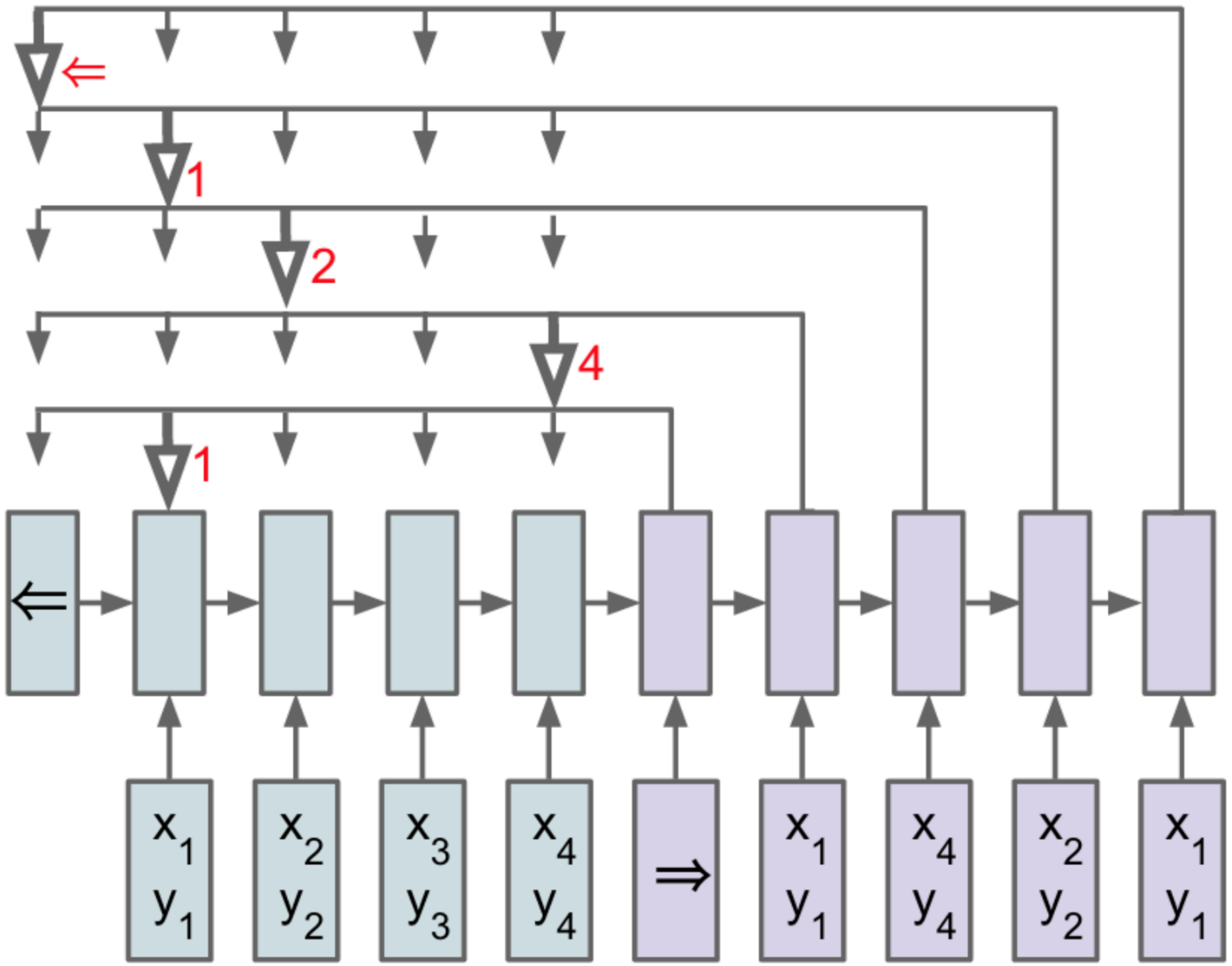
- Bilinear function of input representation + output hidden state

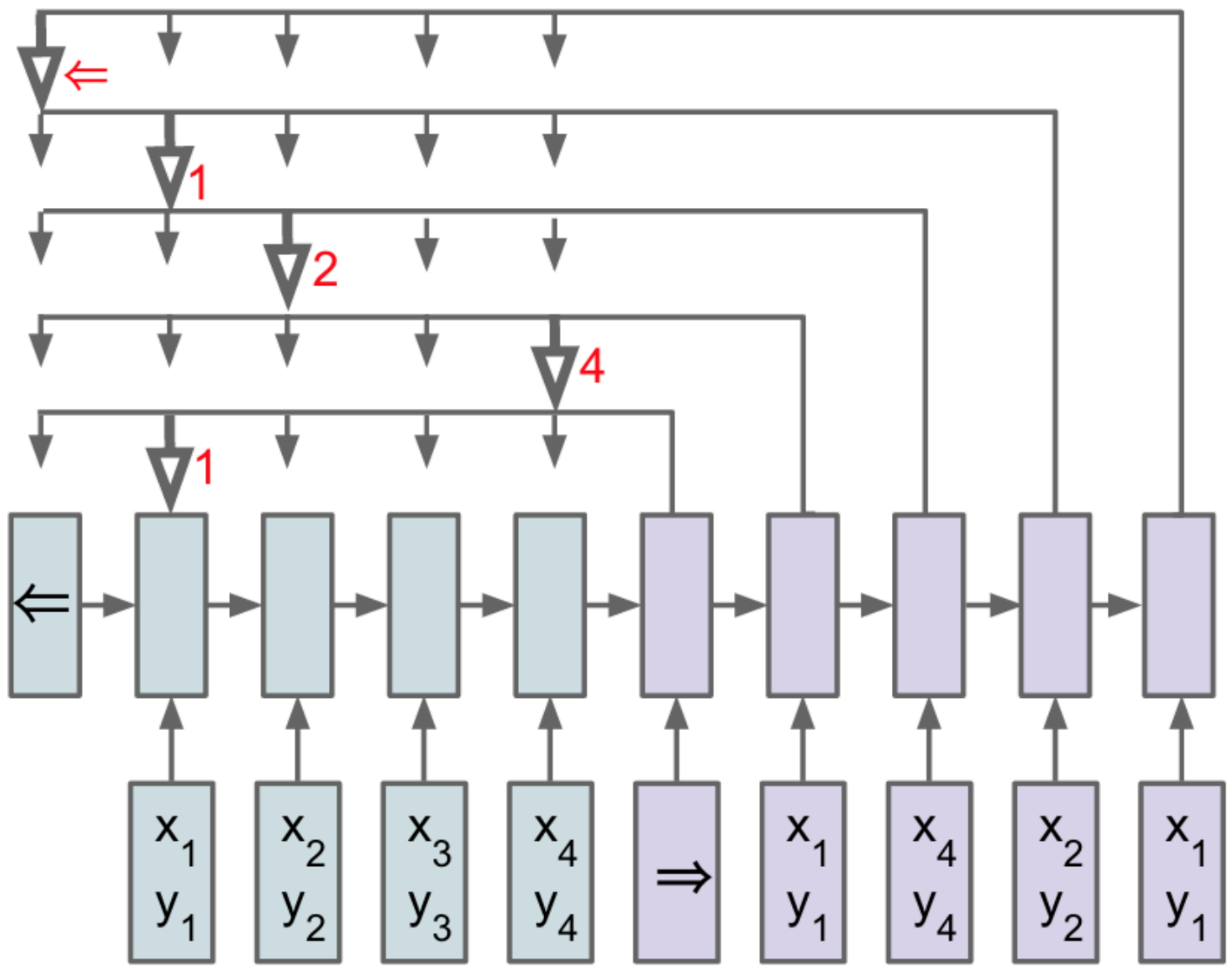
Pointer Networks



Vinyals et al. (2015)

Pointer Networks

- Only point to the input, don't have any notion of vocabulary

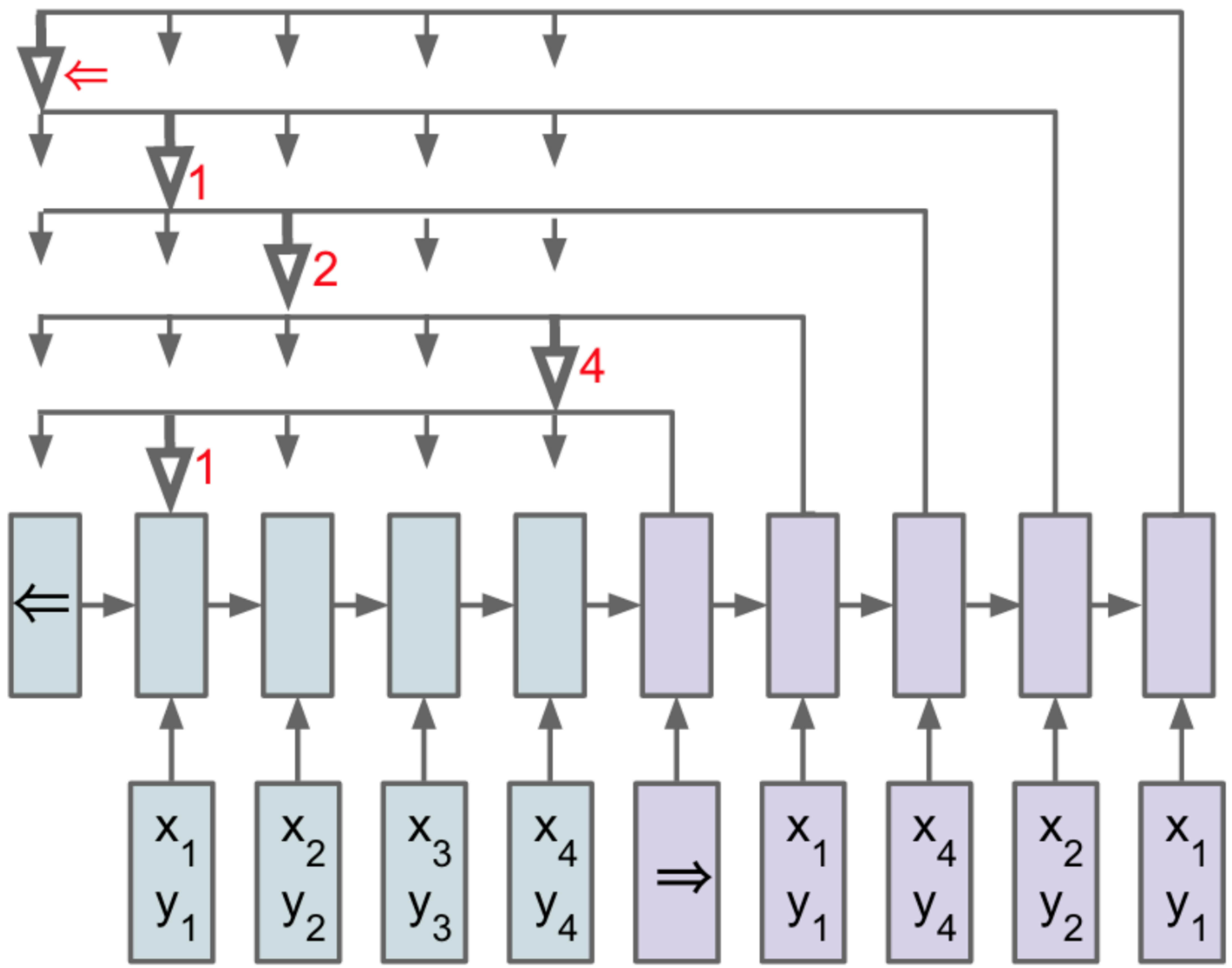


Vinyals et al. (2015)

Pointer Networks

- Only point to the input, don't have any notion of vocabulary

- Used for tasks including summarization and sentence ordering



Vinyals et al. (2015)

Results

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

Jia and Liang (2016)

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Jia and Liang (2016)

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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

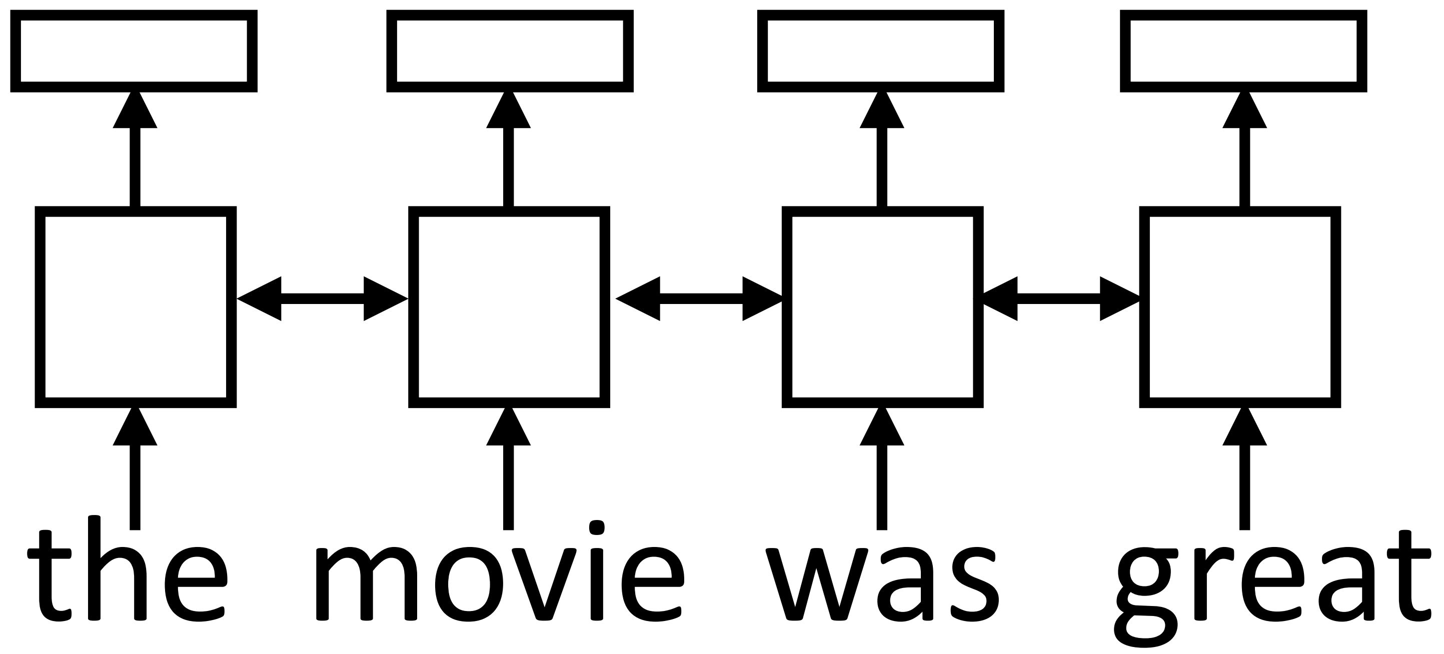
- In many settings, attention can roughly do the same things as copying

Jia and Liang (2016)

Transformers

Self-Attention

- LSTM abstraction: maps each vector in a sentence to a new, context-aware vector



Vaswani et al. (2017)

Self-Attention

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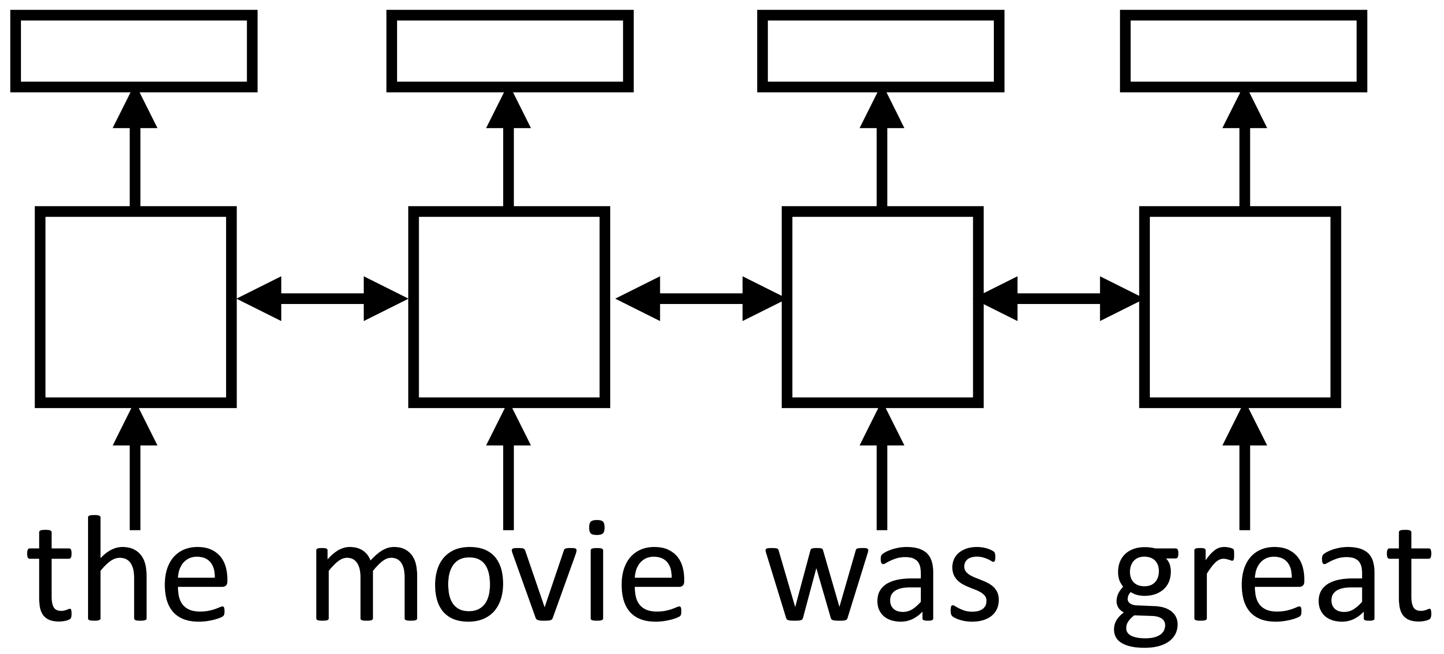

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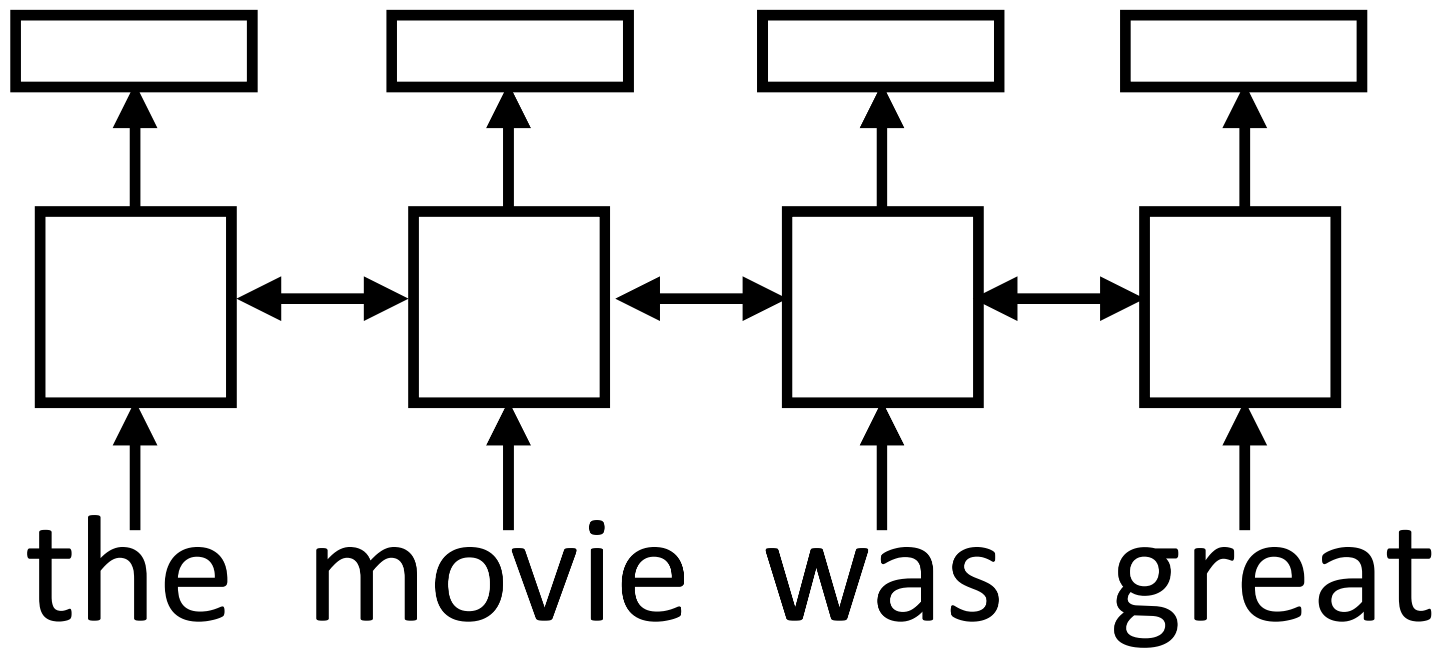
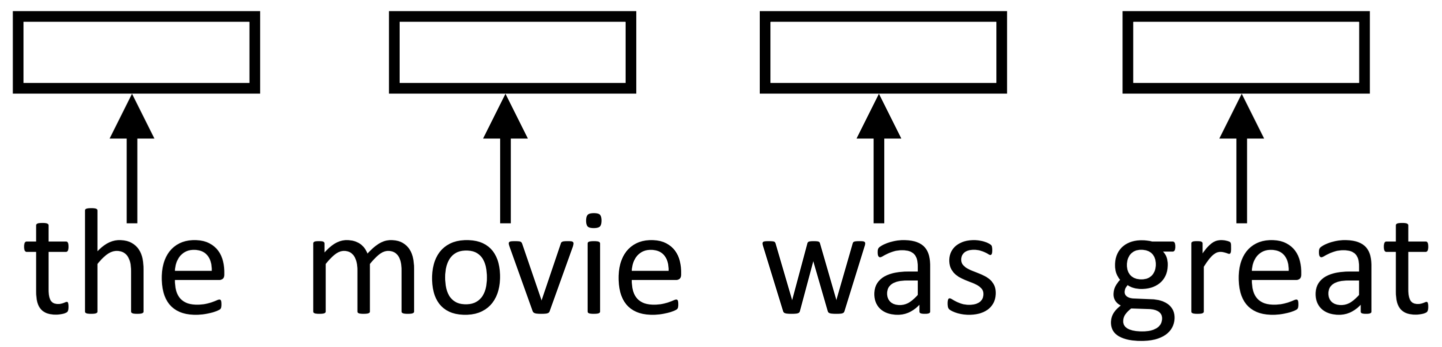


- Attention can give us a third way to do this

Vaswani et al. (2017)

Self-Attention

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



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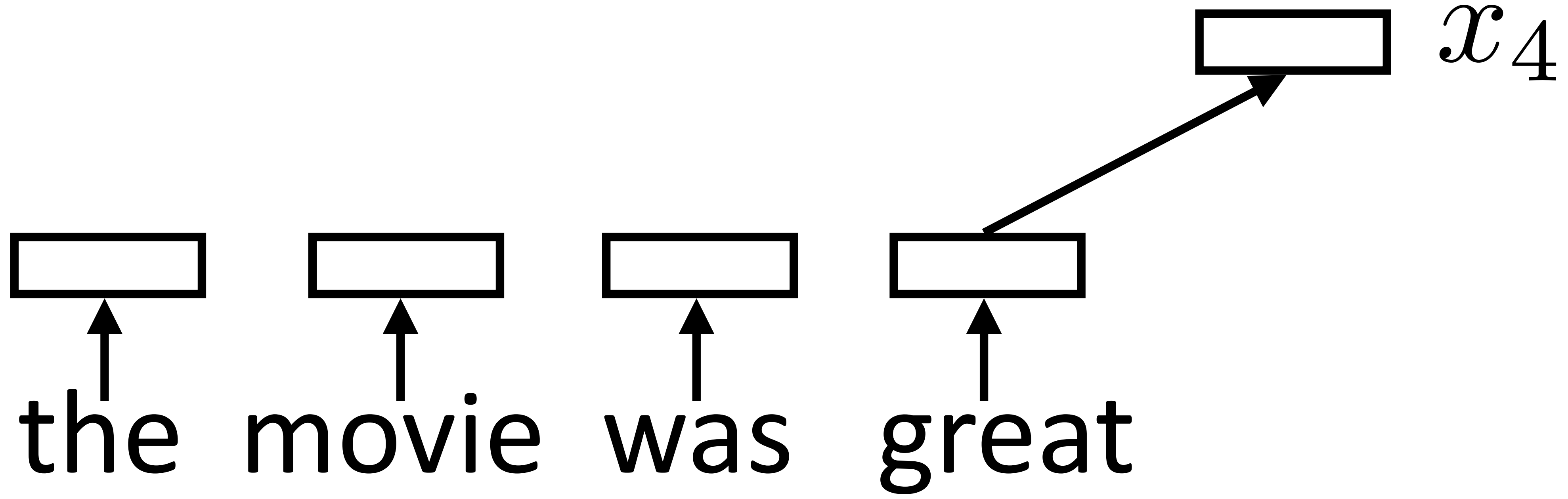

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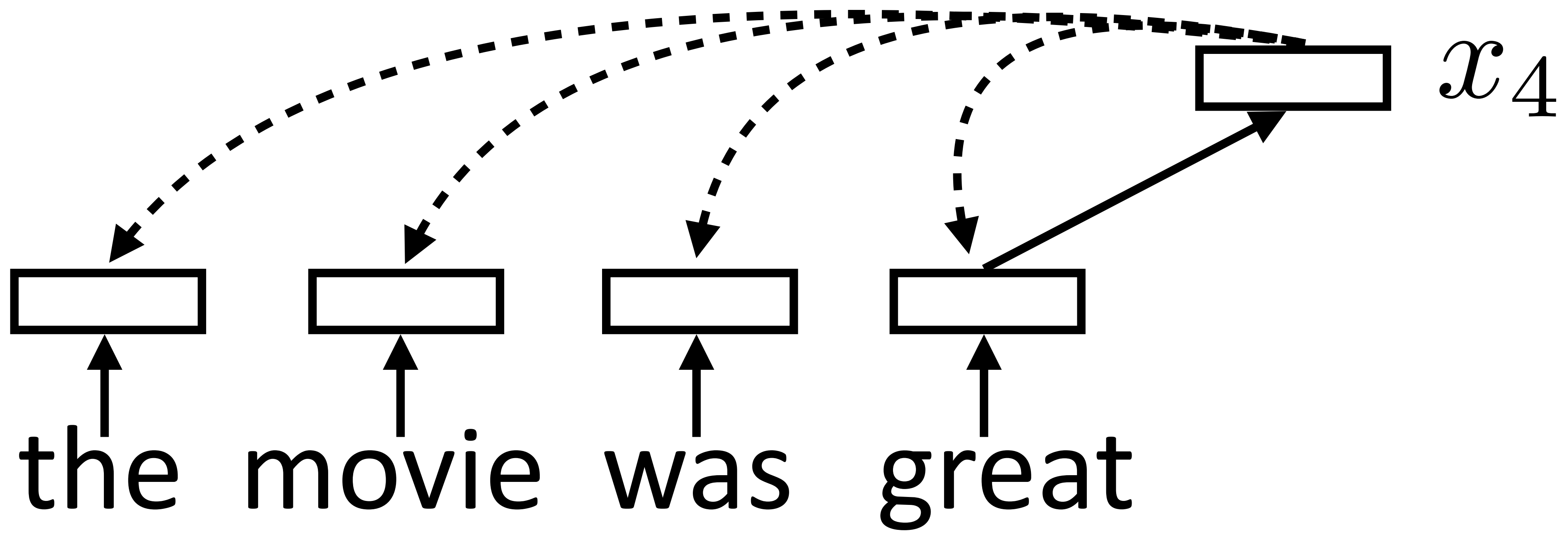

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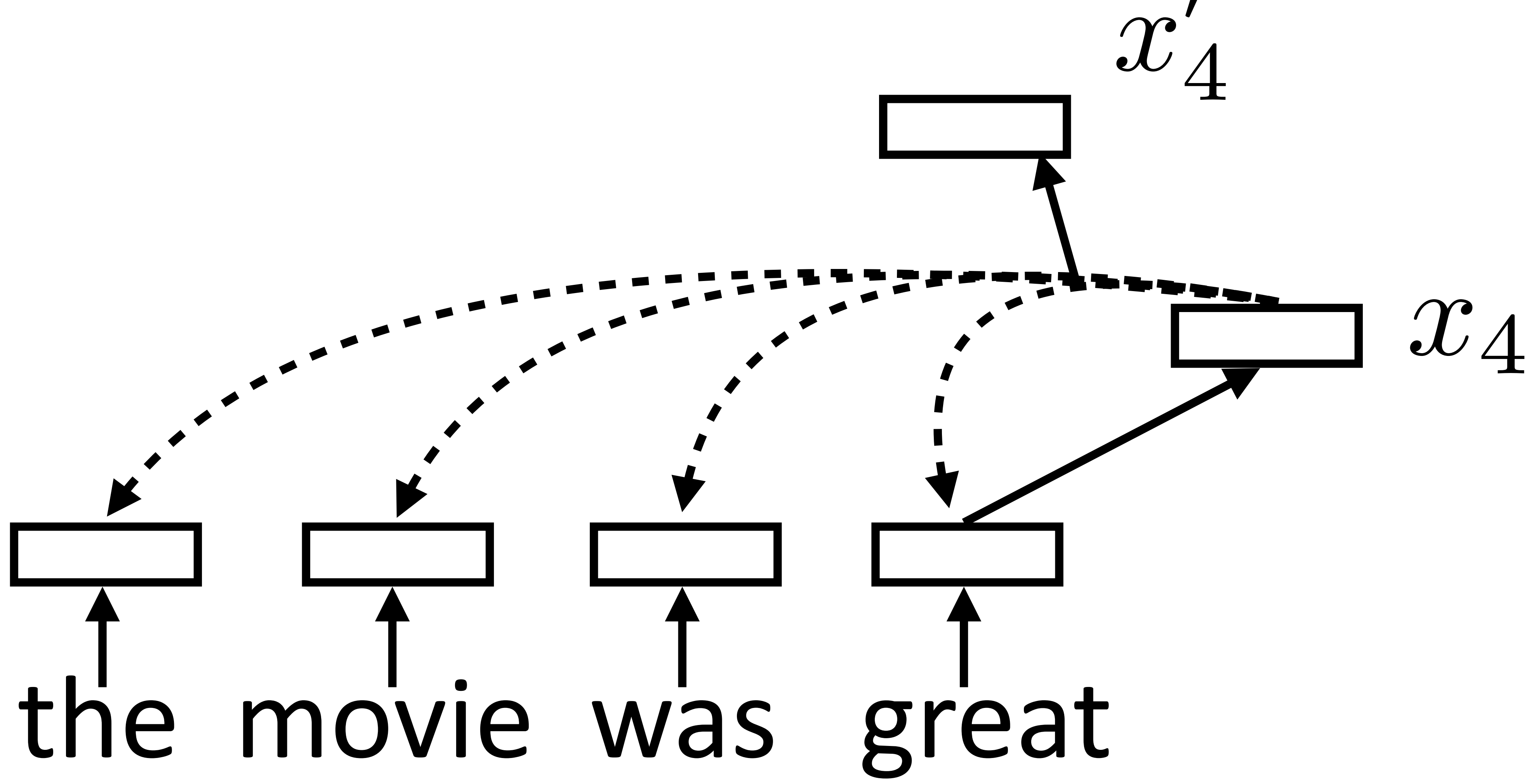

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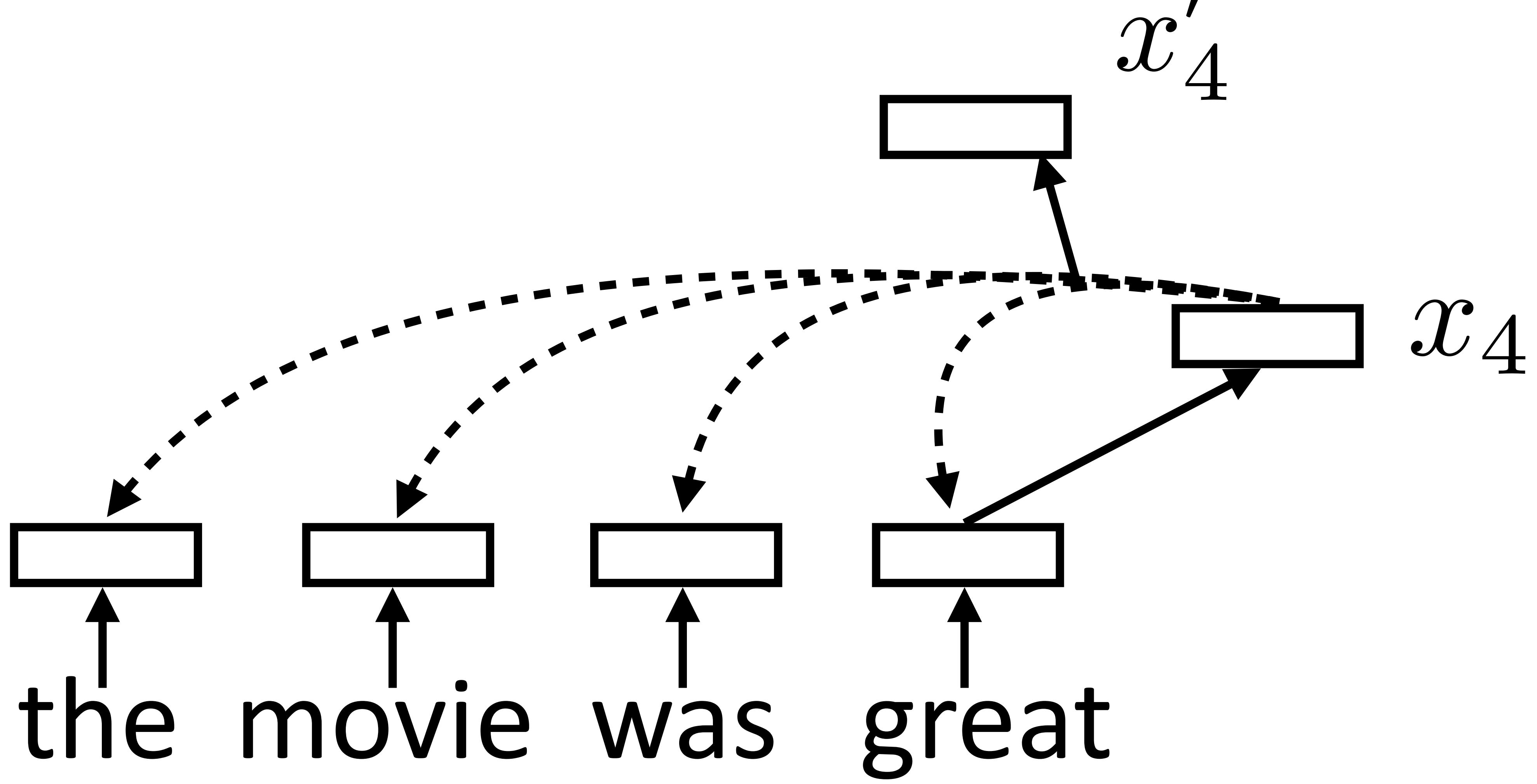
$$\alpha_{i,j} = \mathrm{softmax}(x_i^\top x_j) \quad \text{scalar}$$



Vaswani et al. (2017)

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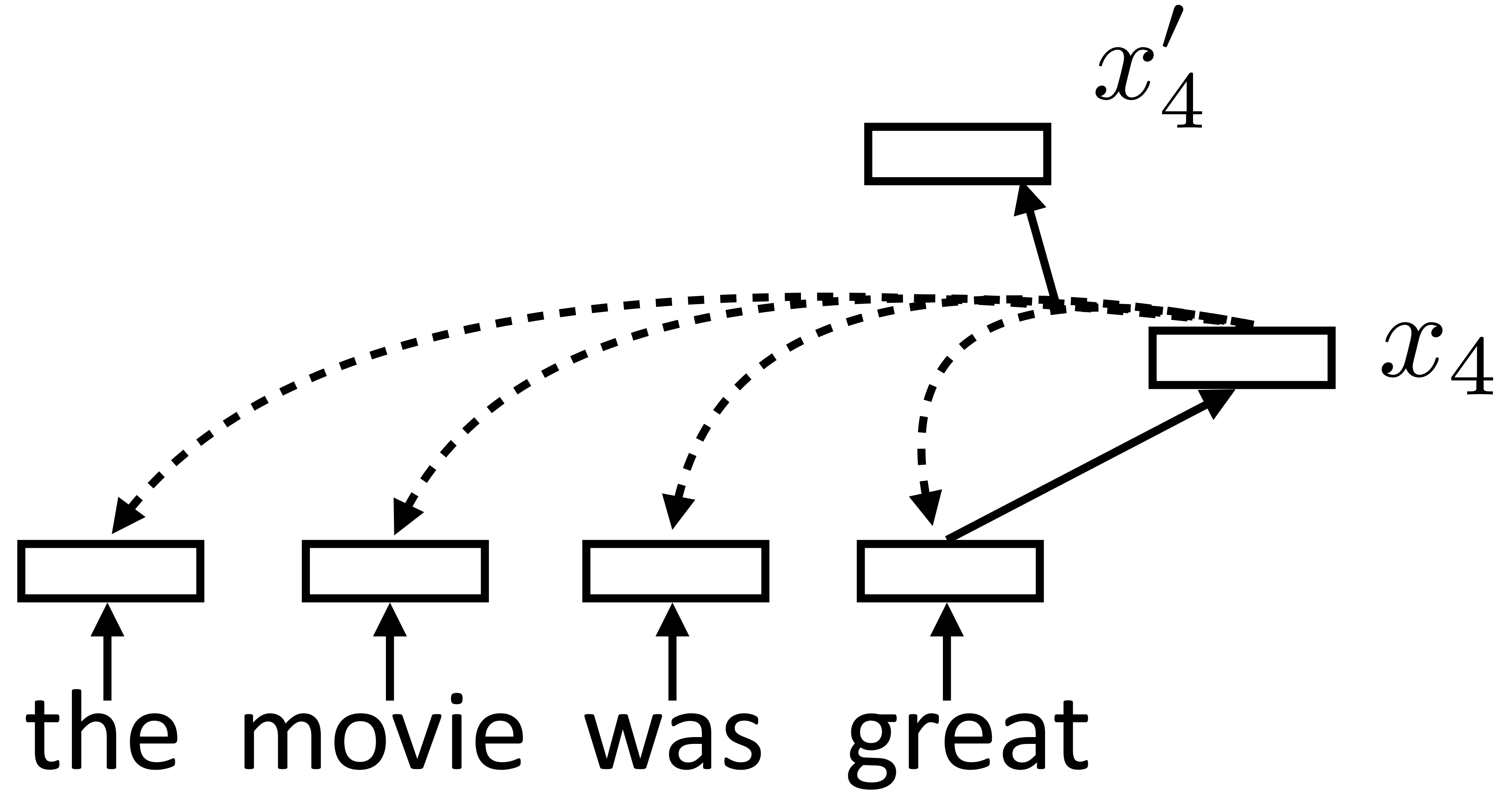

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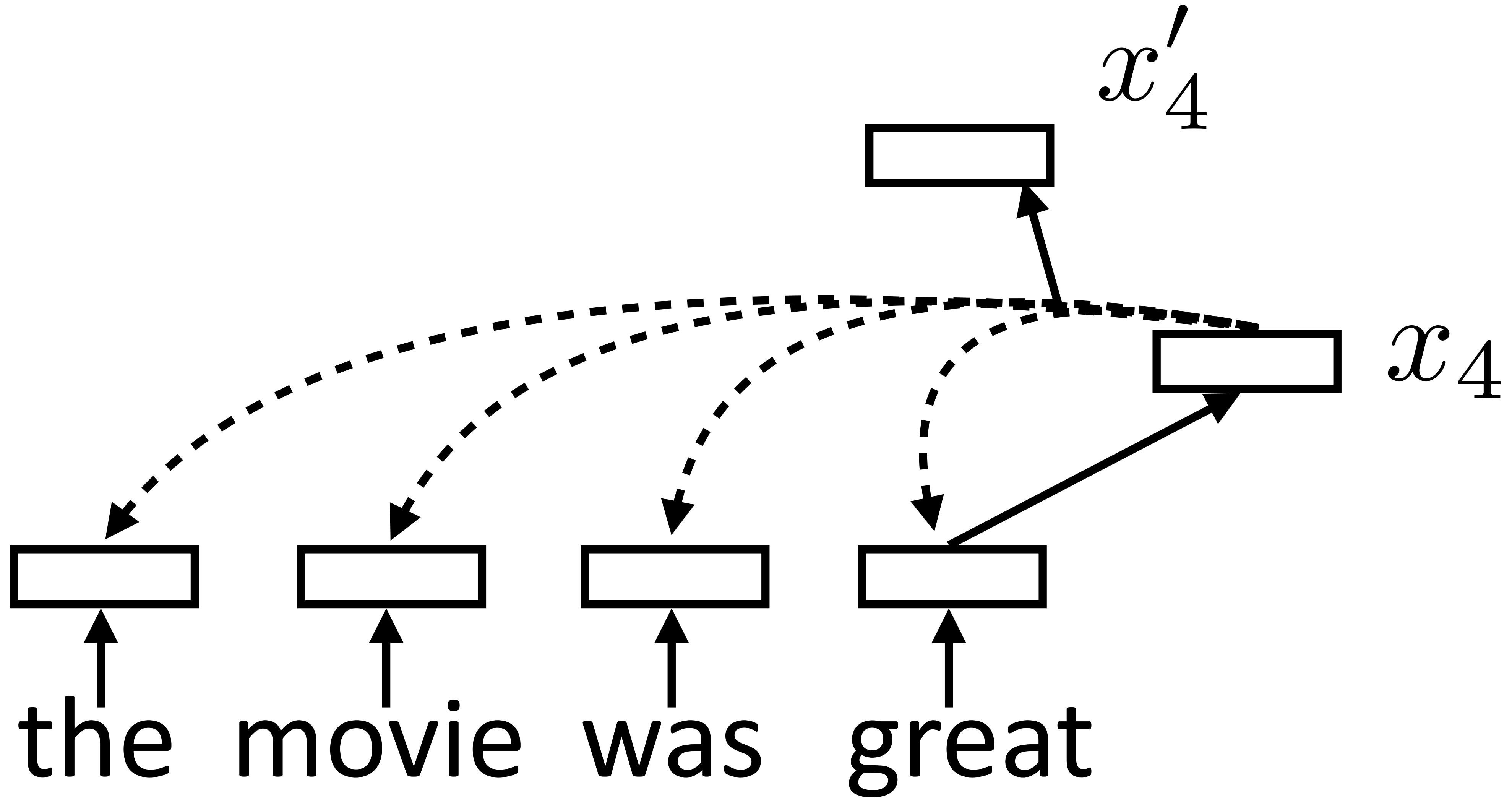

- Multiple "heads" analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

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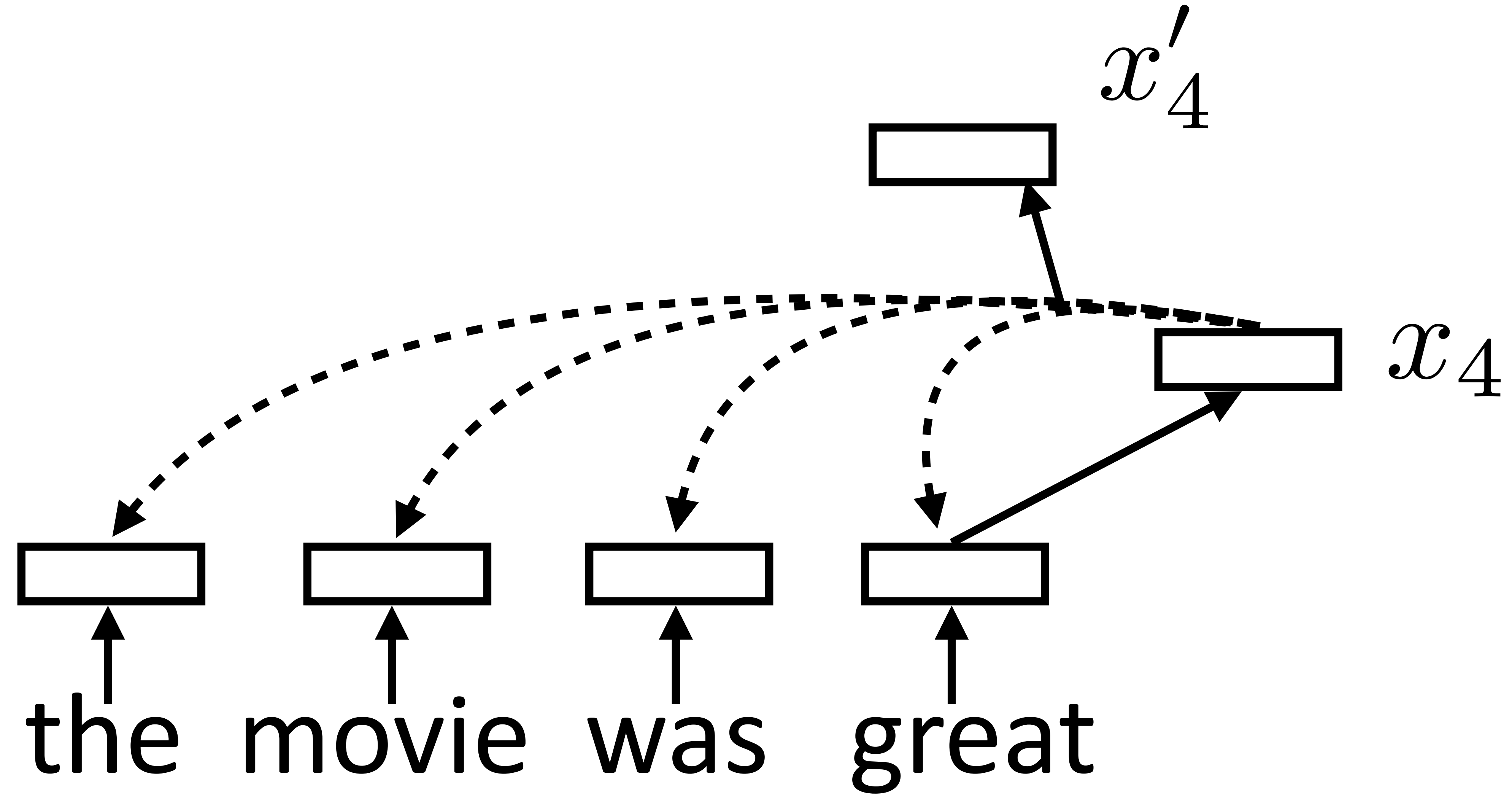

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$$\alpha_{k,i,j} = \text{softmax}(x_i^\top W_k x_j)$$

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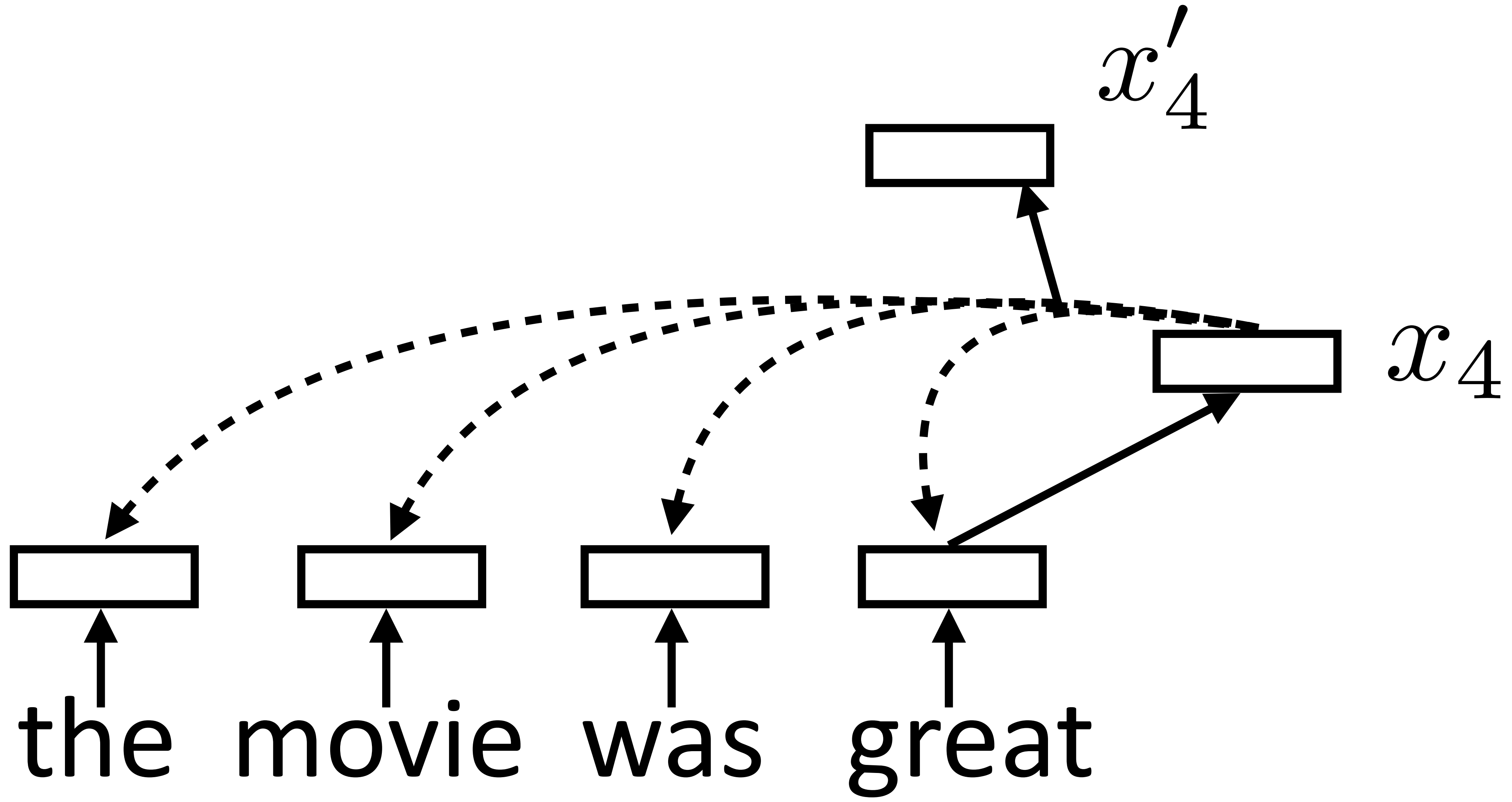

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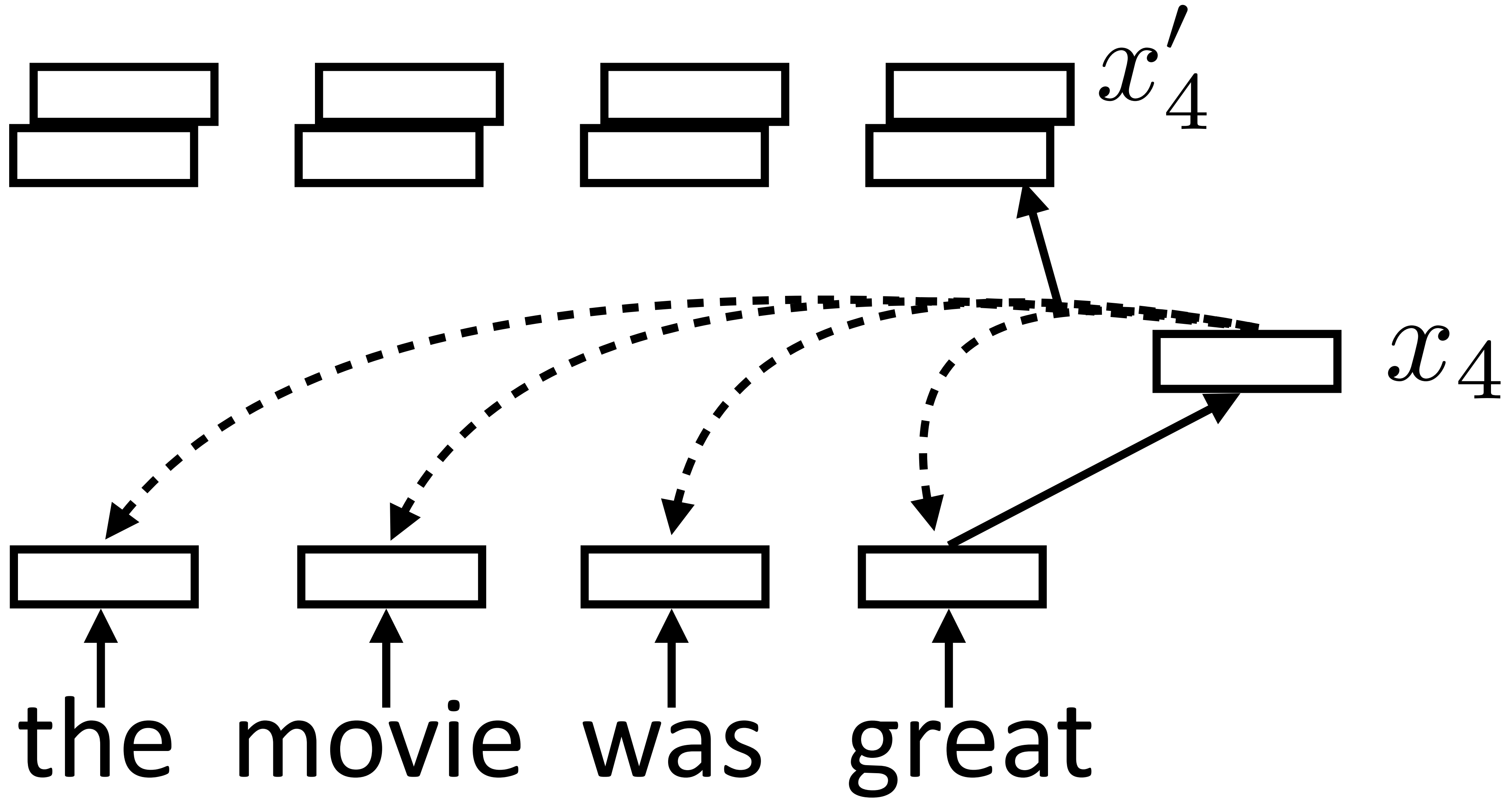

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Vaswani et al. (2017)

Deep Transformers

- Supervised: transformer can replace LSTM; will revisit this when we discuss MT

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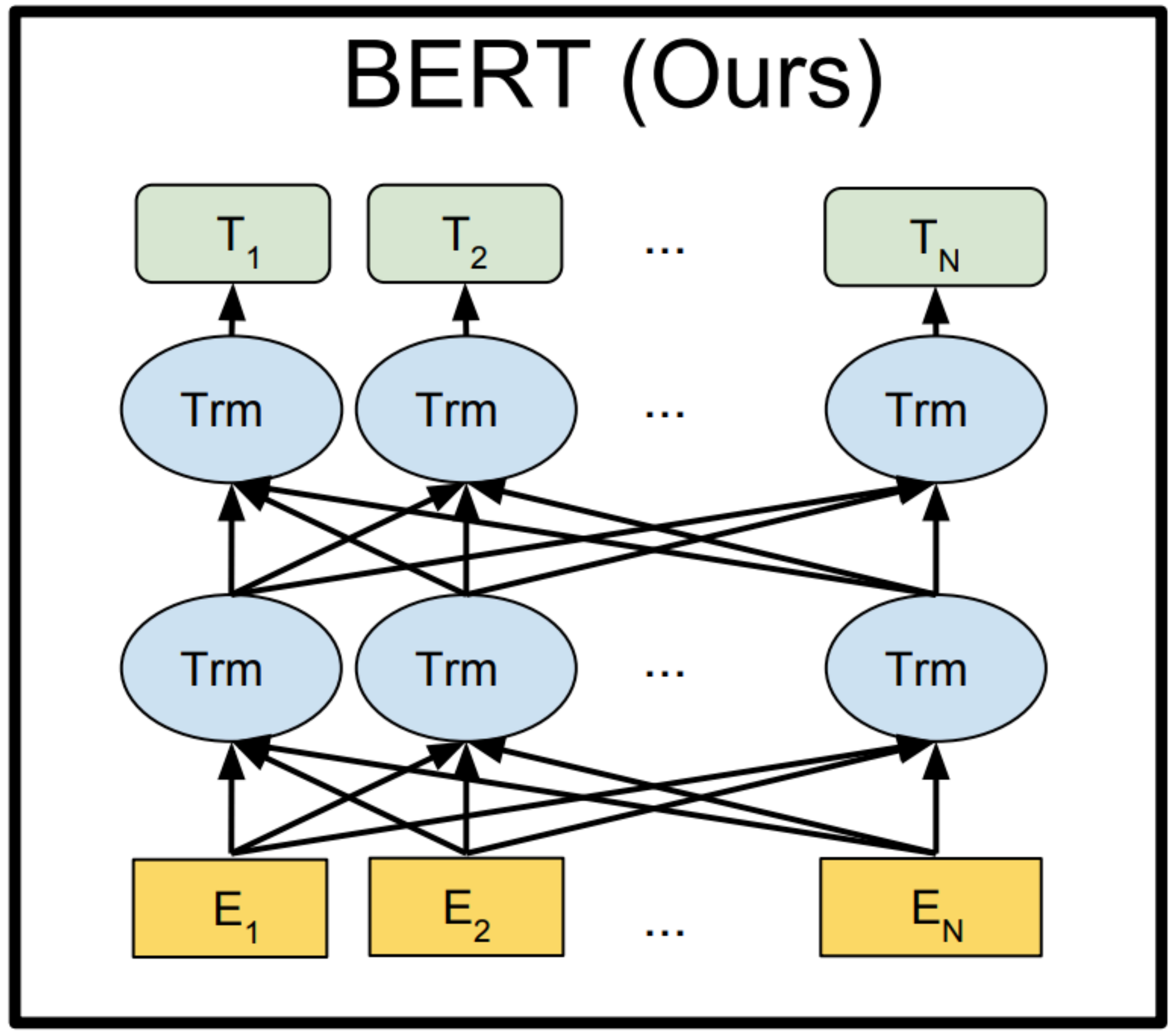

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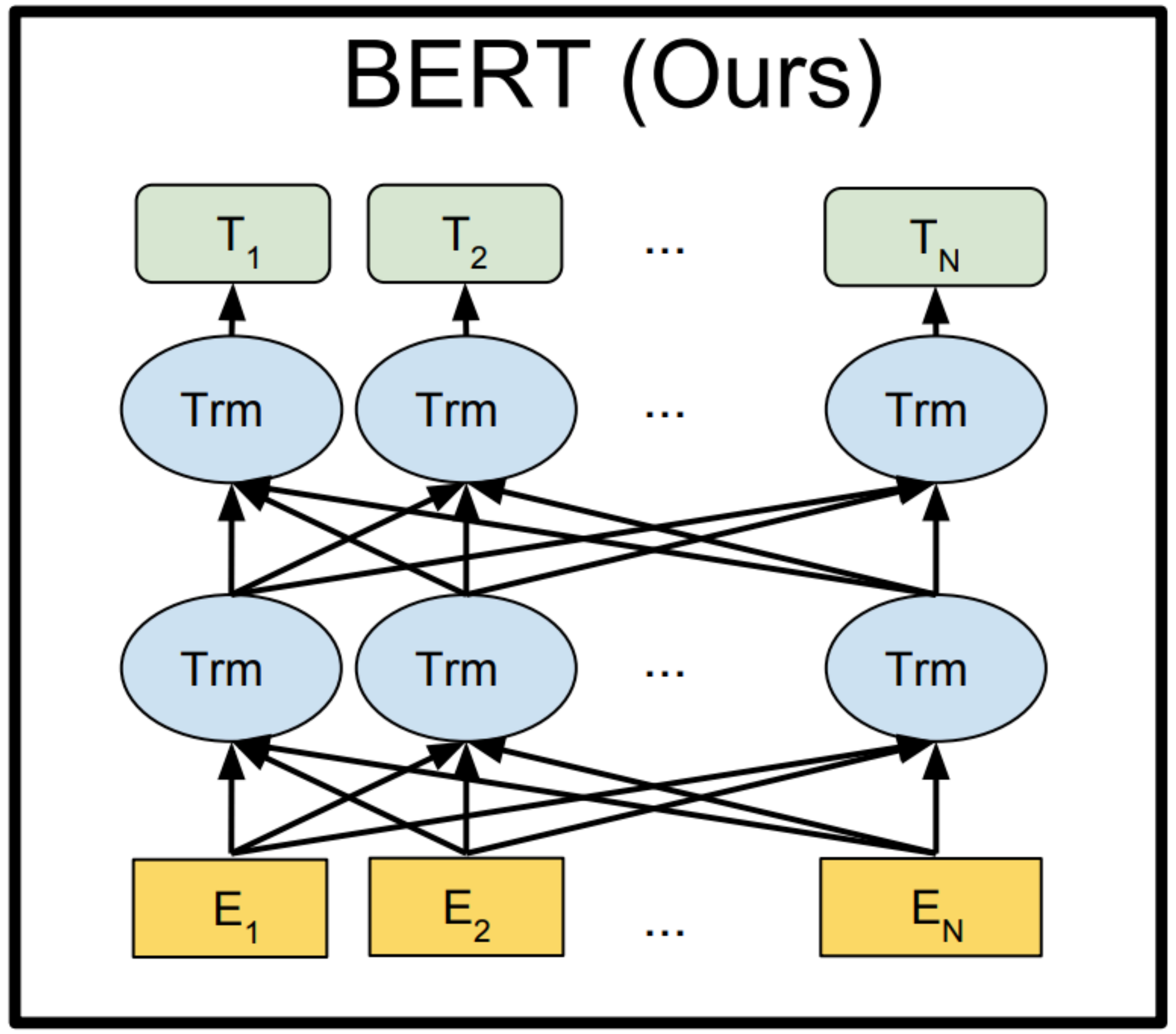
- Stronger than similar methods, SOTA on ~11 tasks (including NER — 92.8 F1)



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- Transformers are strong models we'll come back to later