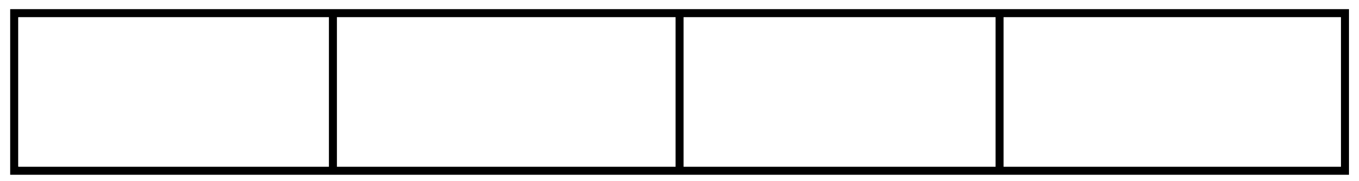
Lecture 11: Seq2Seq + Attention

Alan Ritter

(many slides from Greg Durrett)

Recall: CNNs vs. LSTMs



n x k

the movie was good

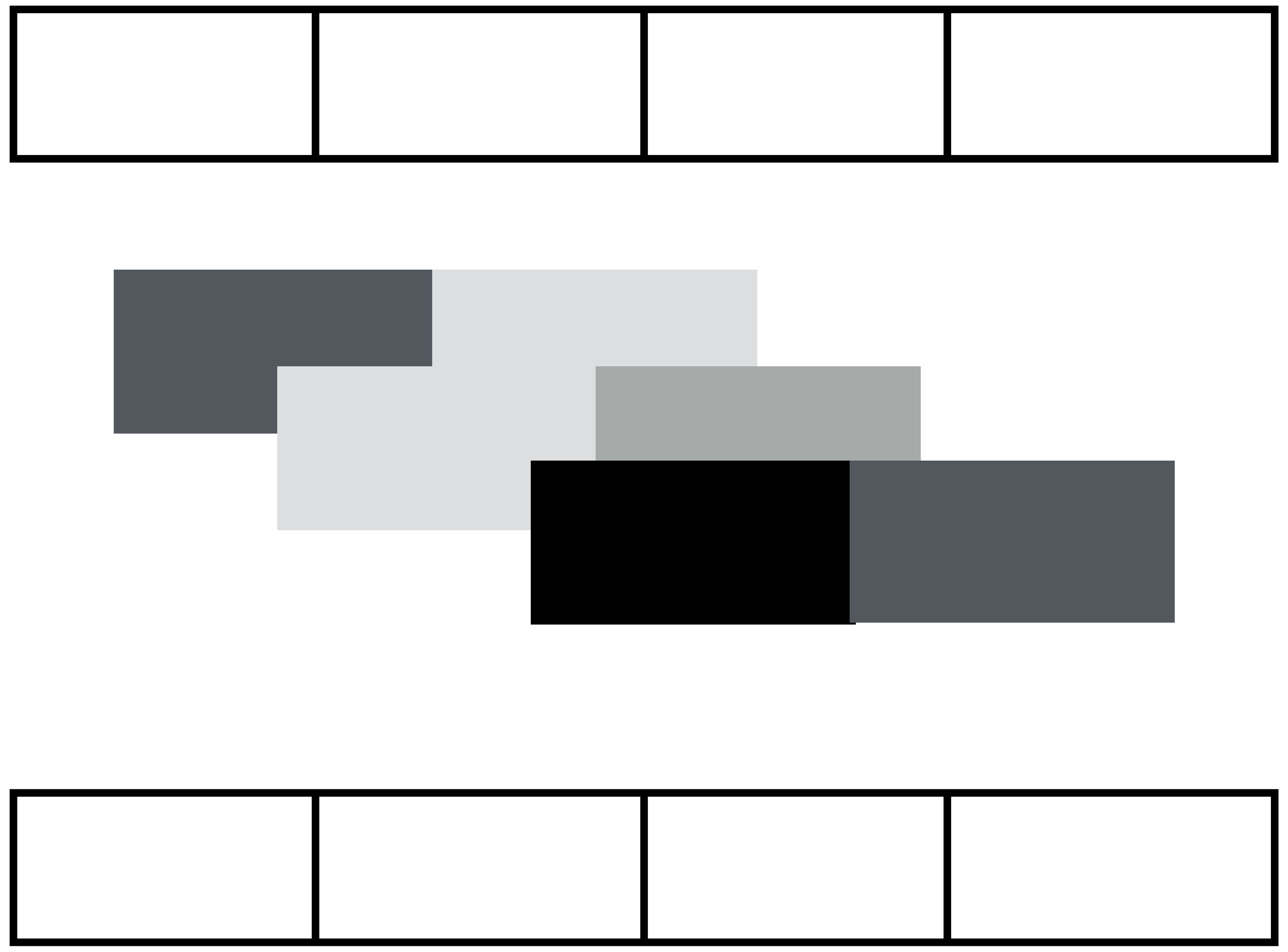
Recall: CNNs vs. LSTMs

c filters,
m x k each

n x k

the movie was good

Recall: CNNs vs. LSTMs



O(n) x c

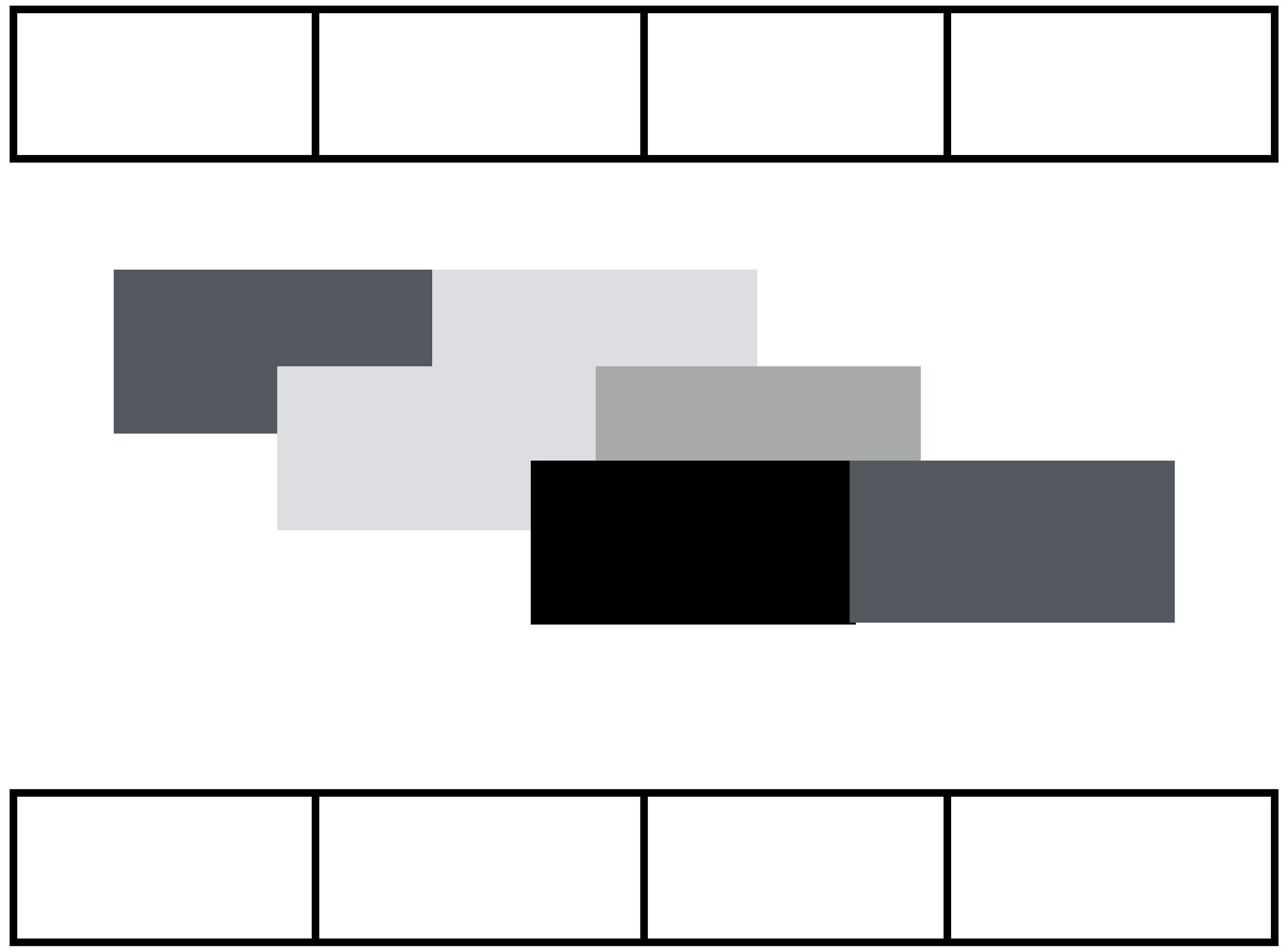
c filters,

m x k each

n x k

the movie was good

Recall: CNNs vs. LSTMs

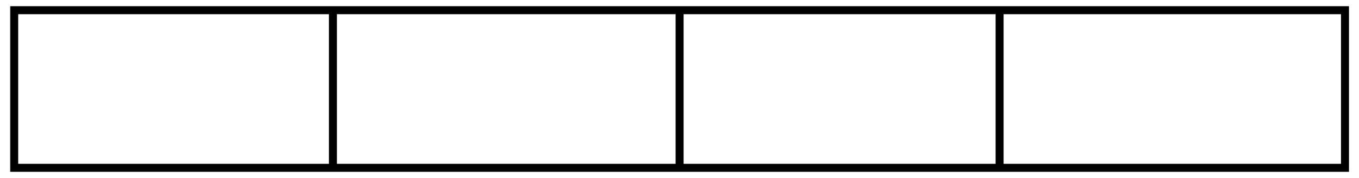


O(n) x c

c filters,
m x k each

n x k

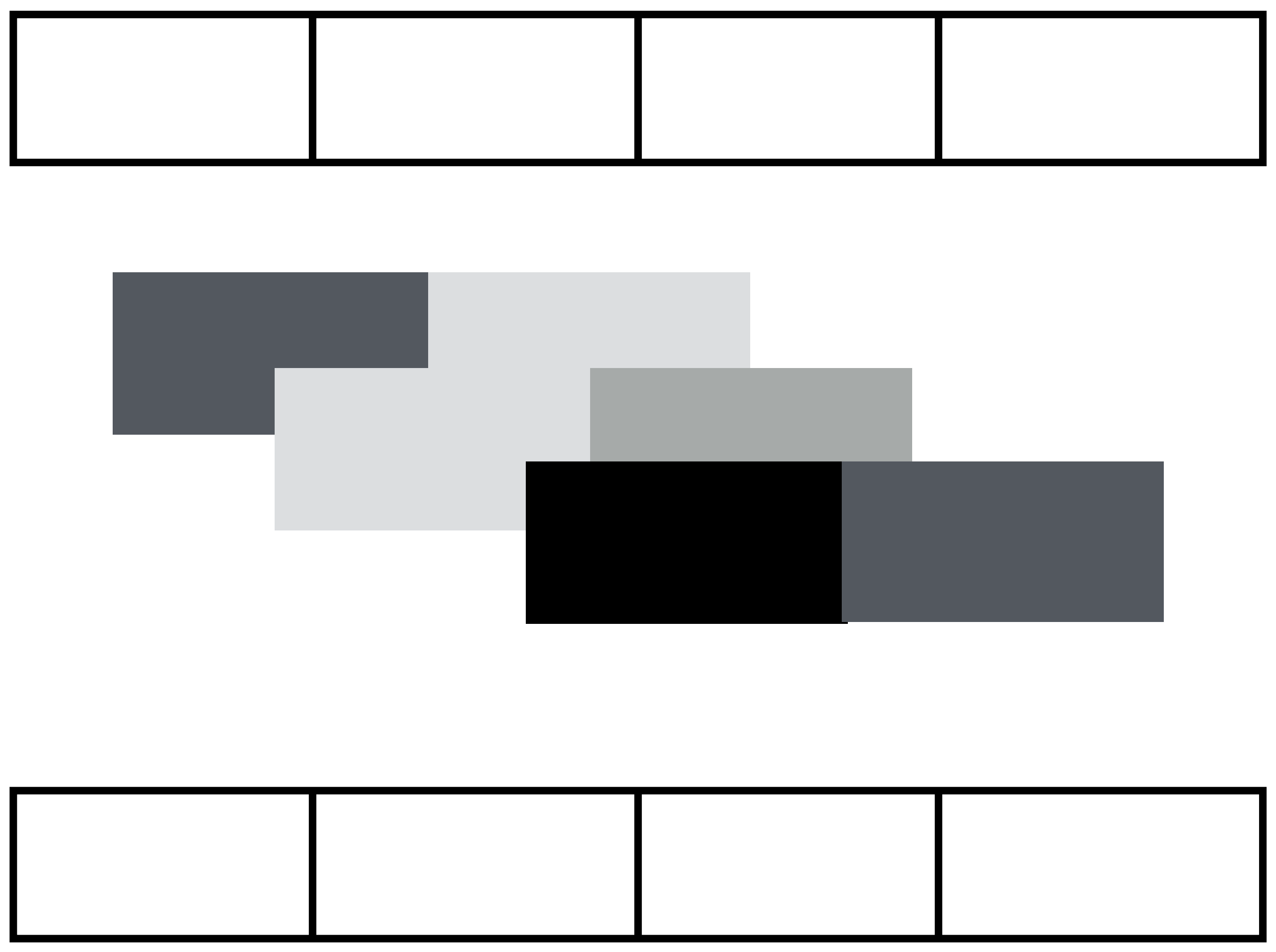
the movie was good

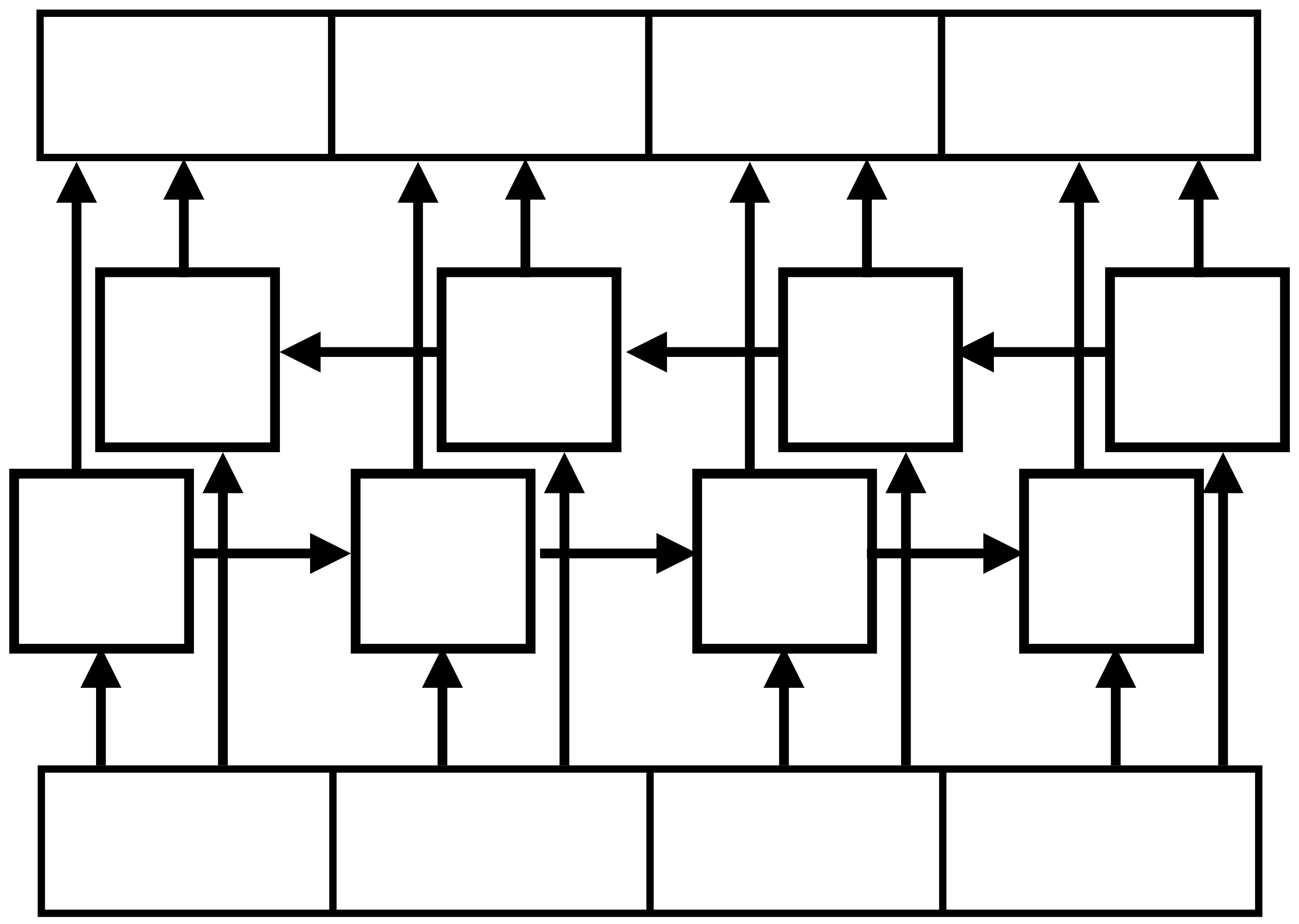


n x k

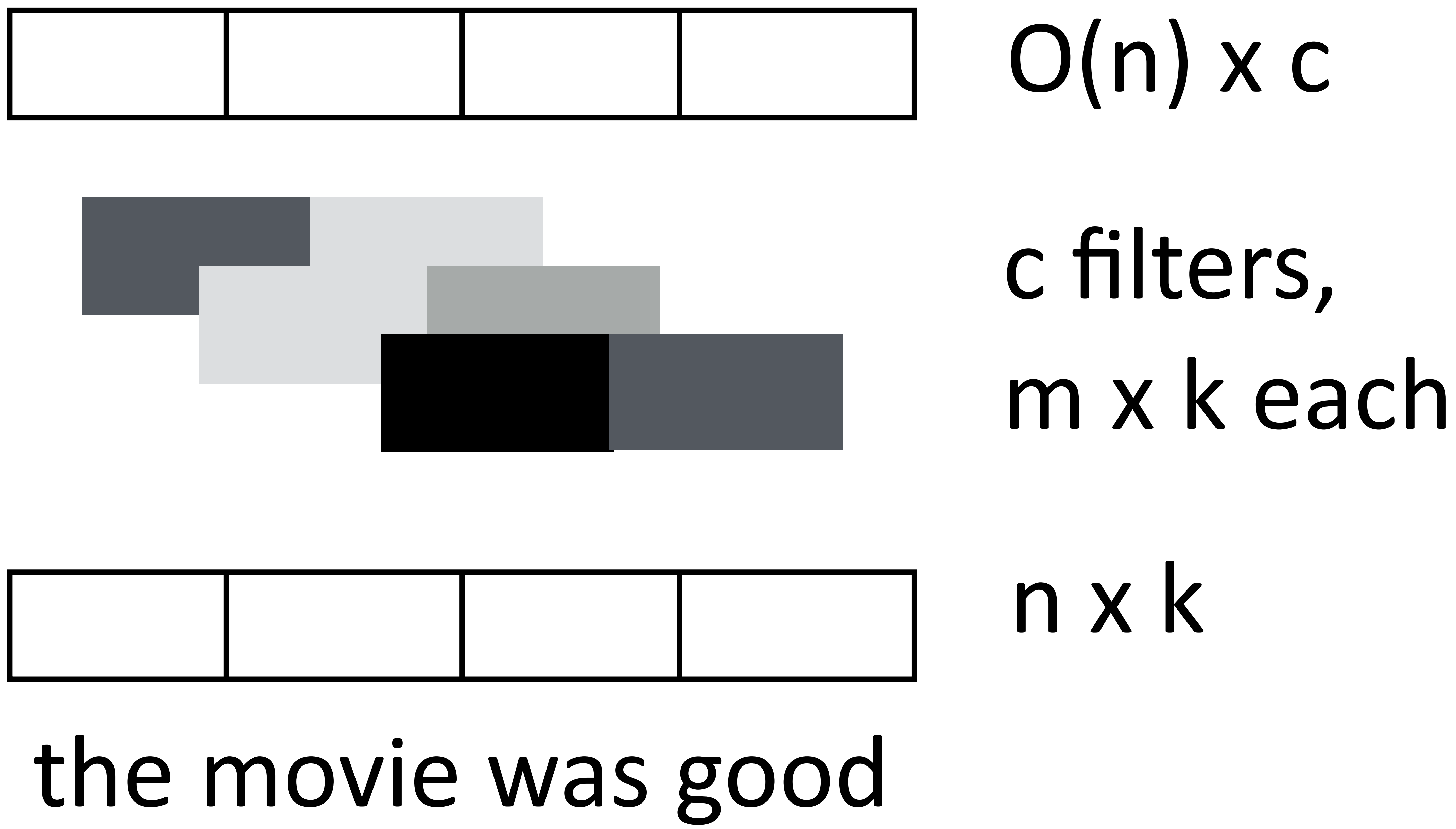
the movie was good

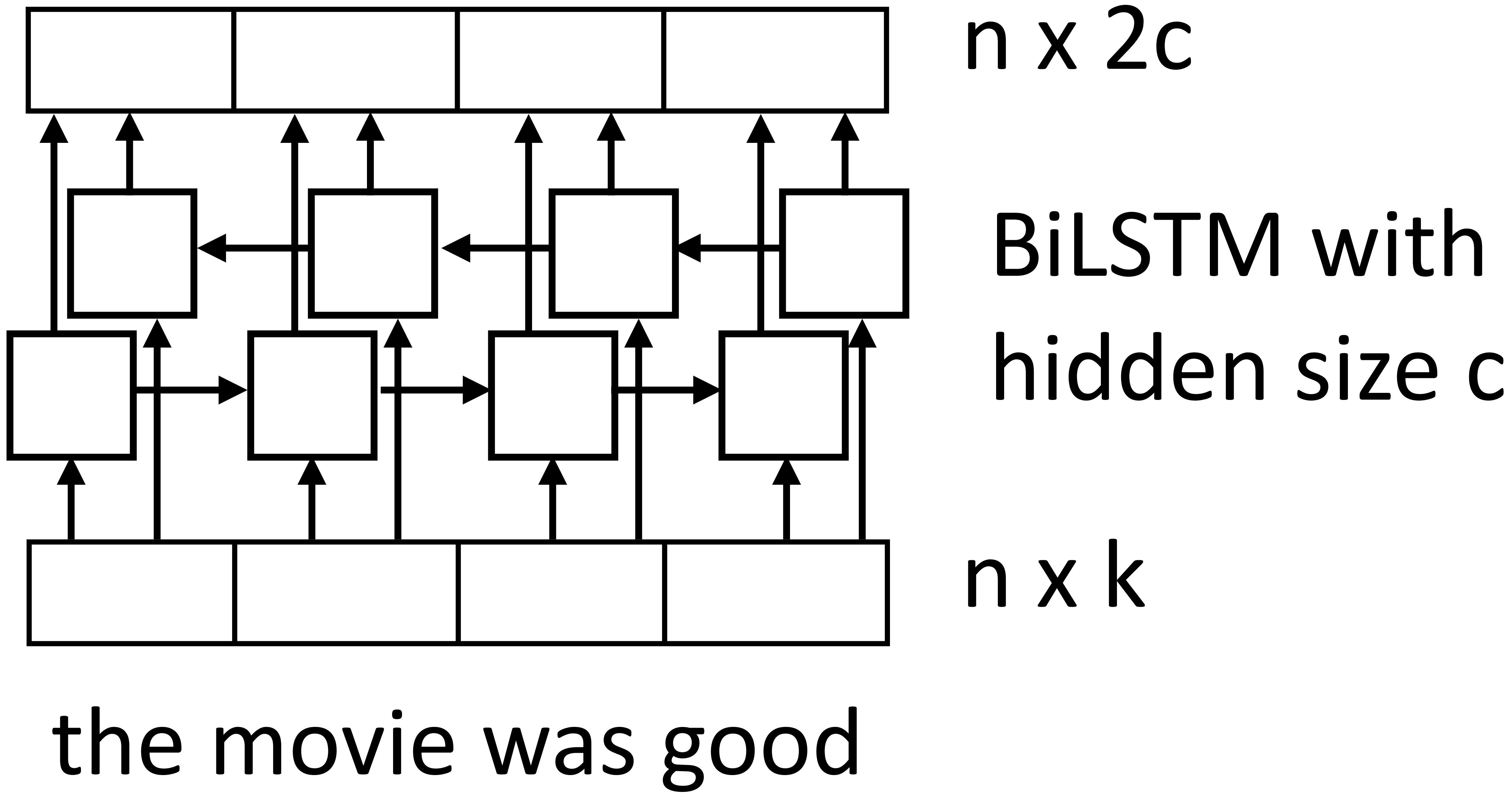
Recall: CNNs vs. LSTMs





Recall: CNNs vs. LSTMs

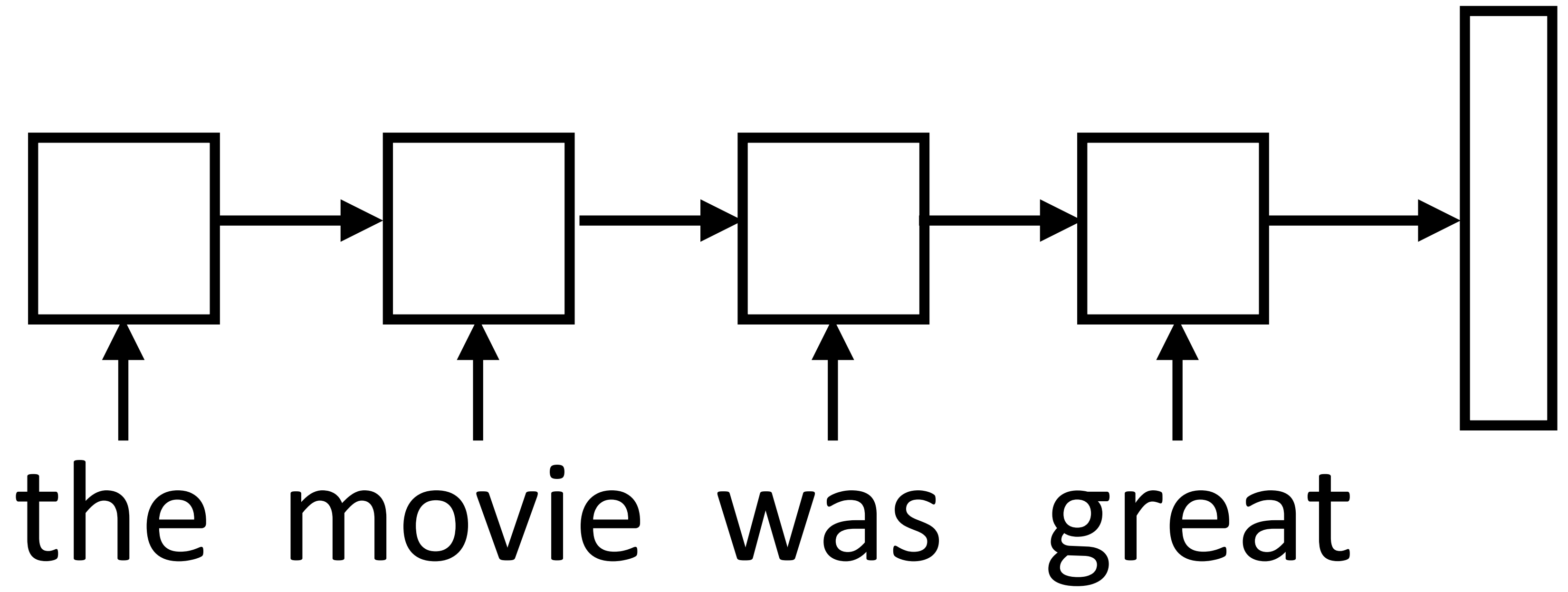




- Both LSTMs and convolutional layers transform the input using context
- LSTM: “globally” looks at the entire sentence (but local for many problems)
- CNN: local depending on filter width + number of layers

Encoder-Decoder

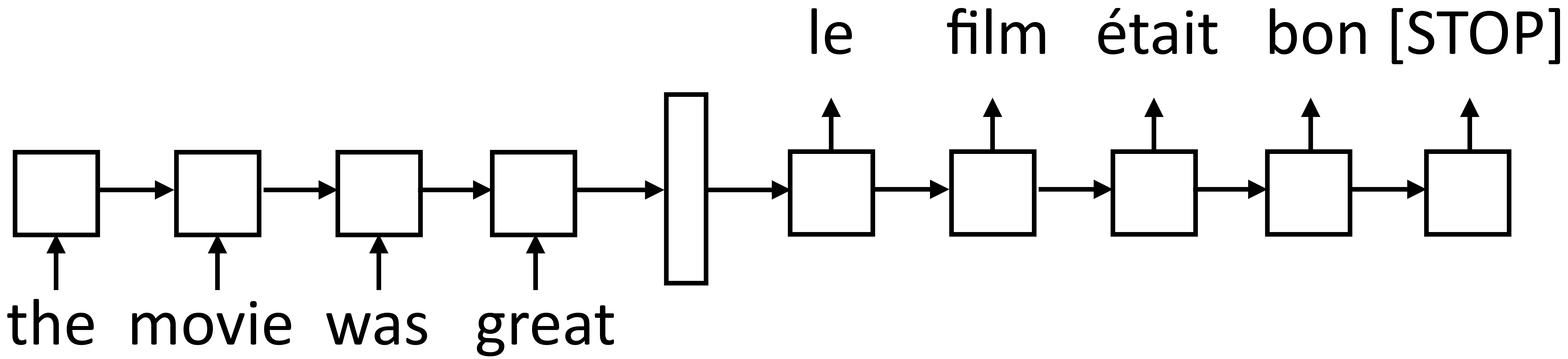
- Encode a sequence into a fixed-sized vector



Sutskever et al. (2014)

Encoder-Decoder

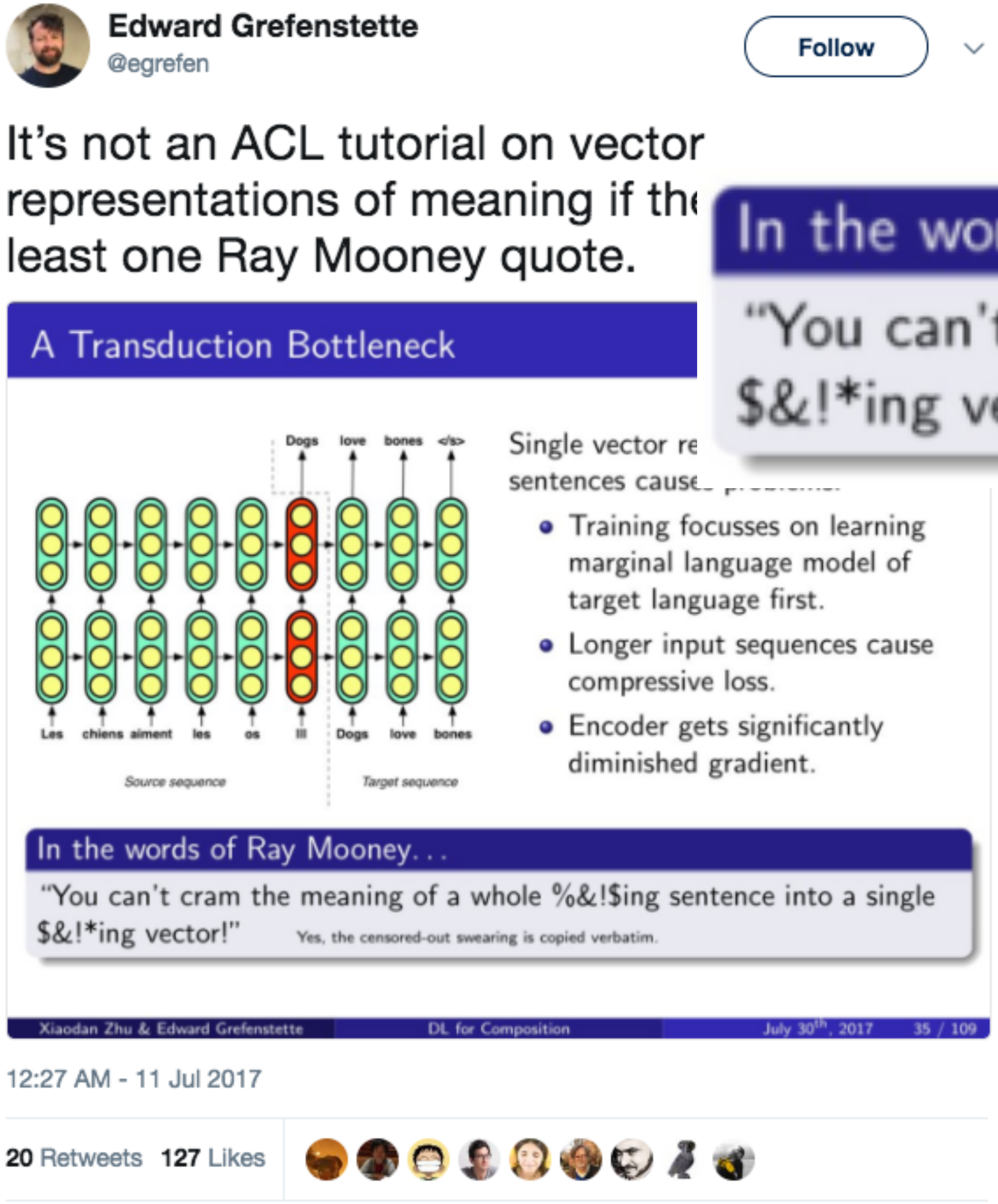
- Encode a sequence into a fixed-sized vector

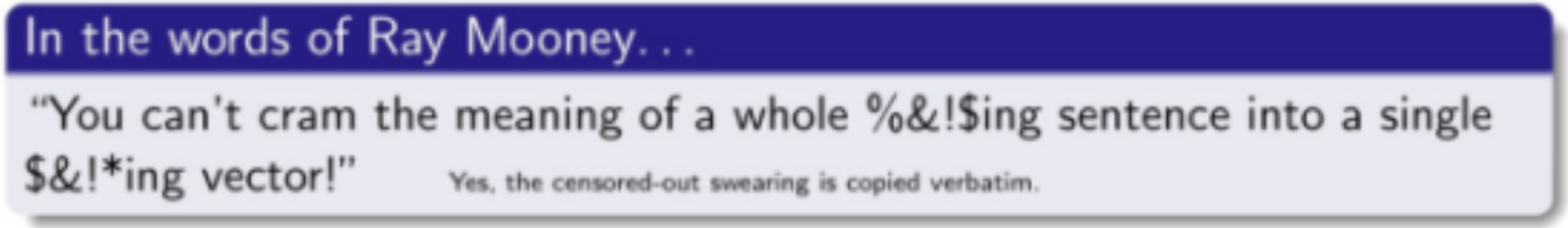


- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

Encoder-Decoder

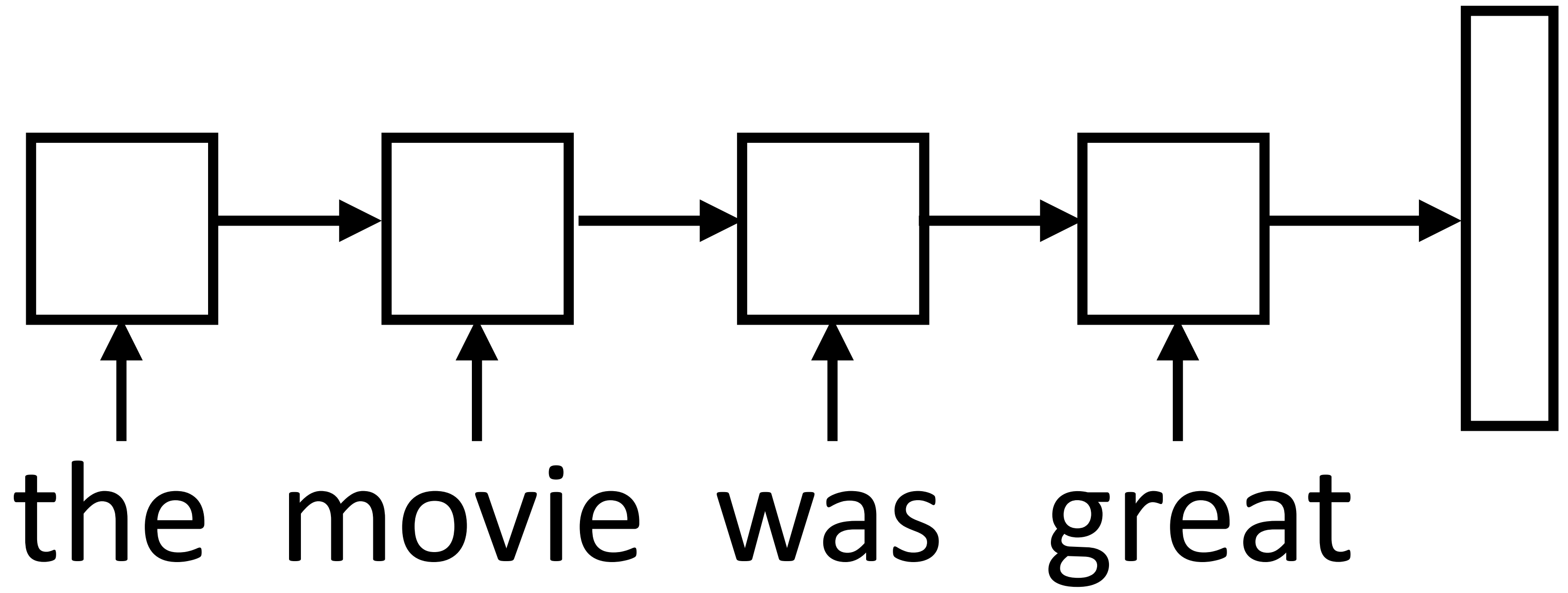




- Is this true? Sort of…we'll come back to this later

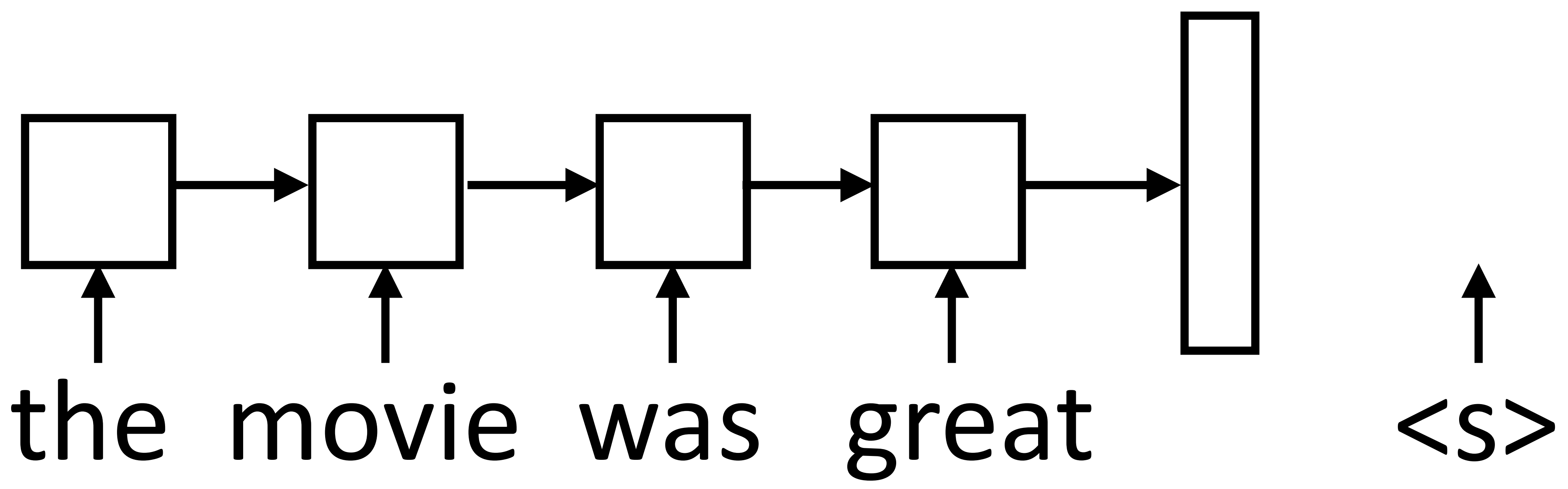
Model

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



Model

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

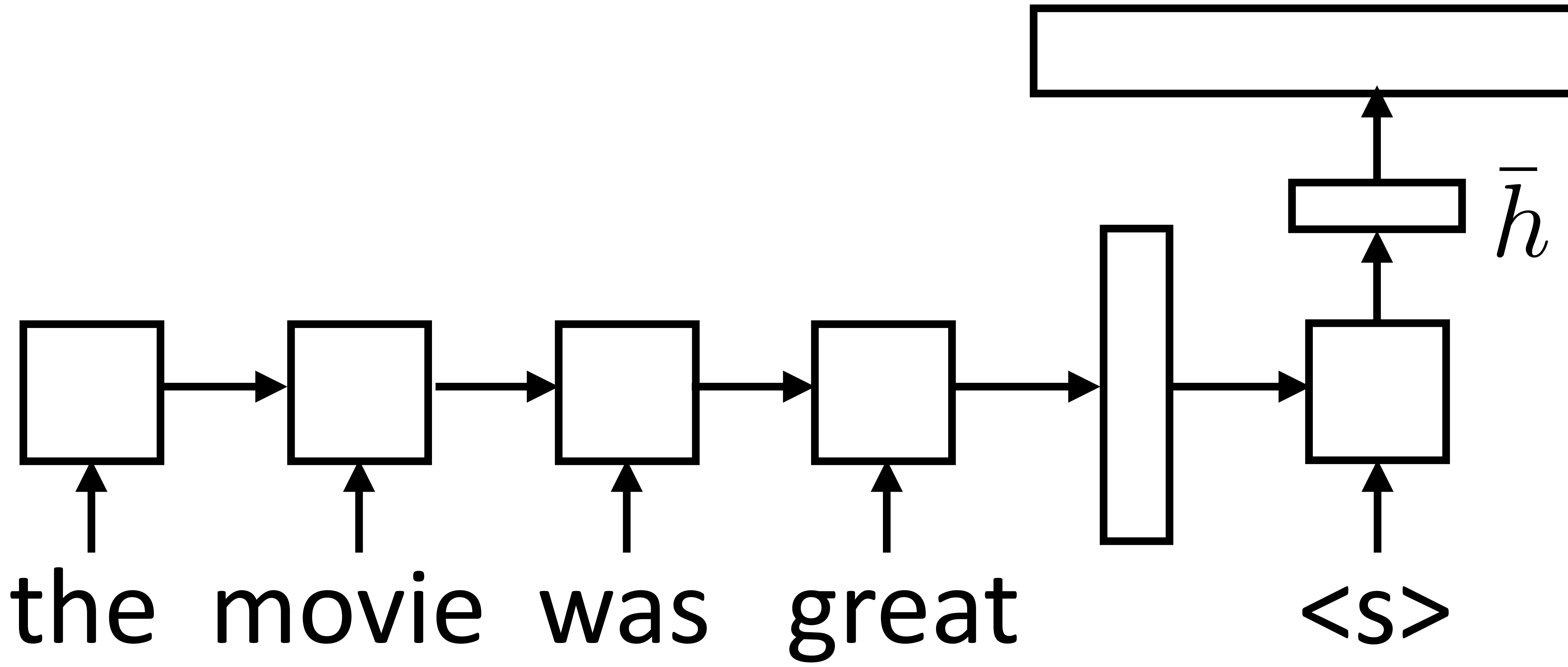


Model

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

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

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



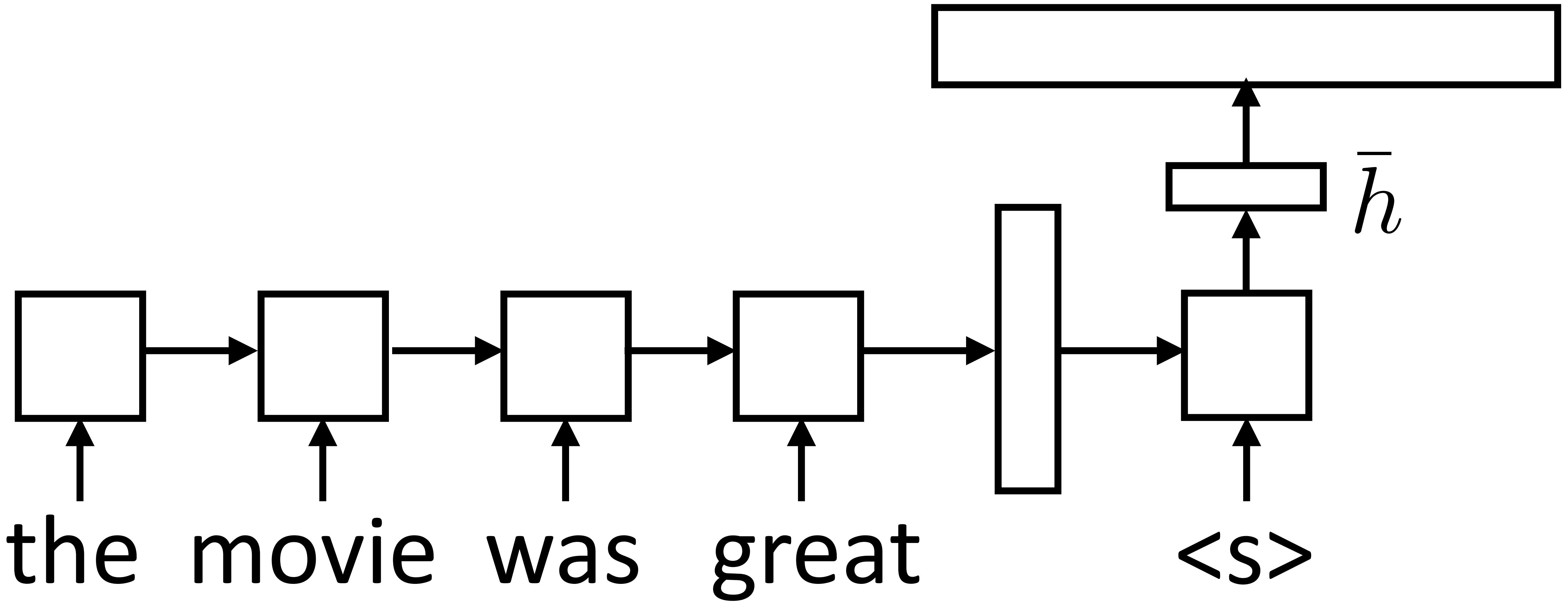
Model

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

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

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

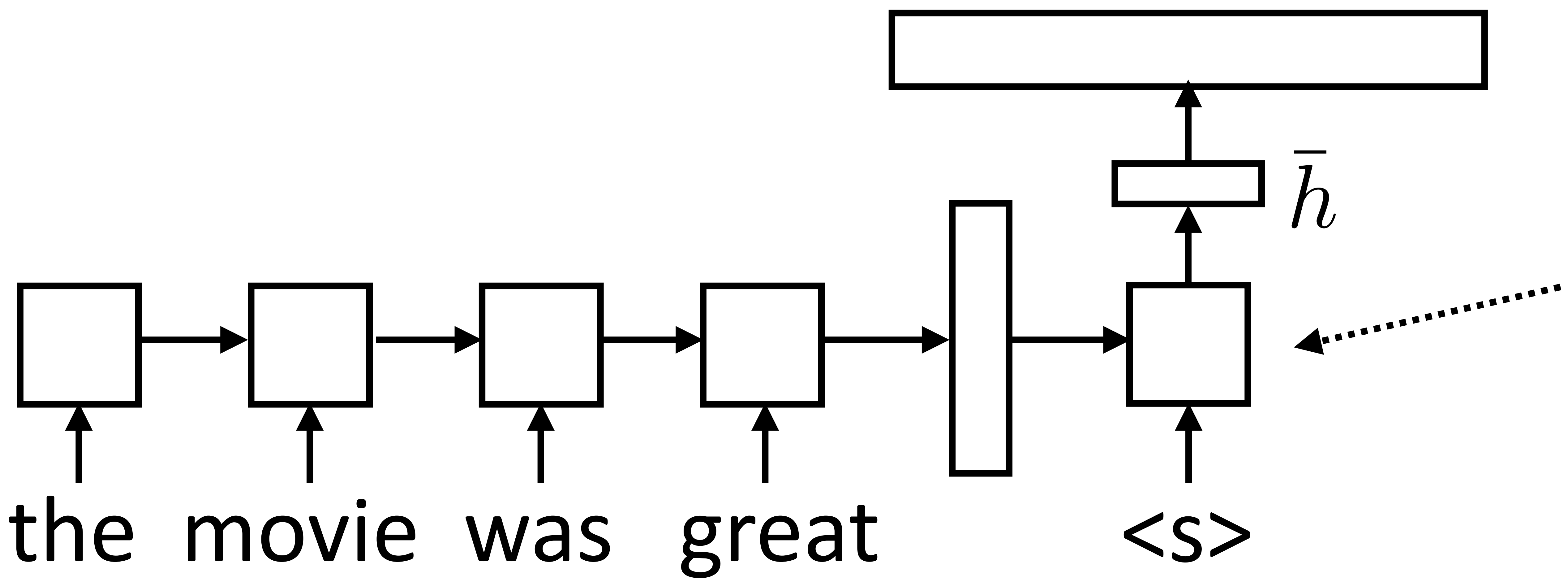
$$P(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{n} P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1})$$



Model

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

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



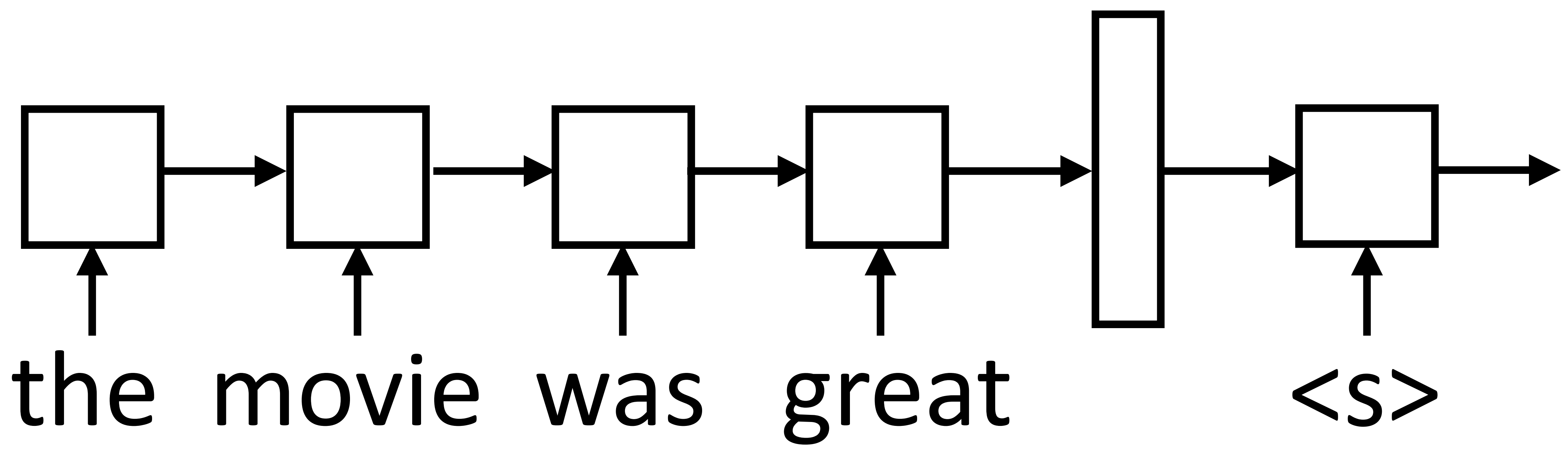
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W\bar{h})$$

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

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

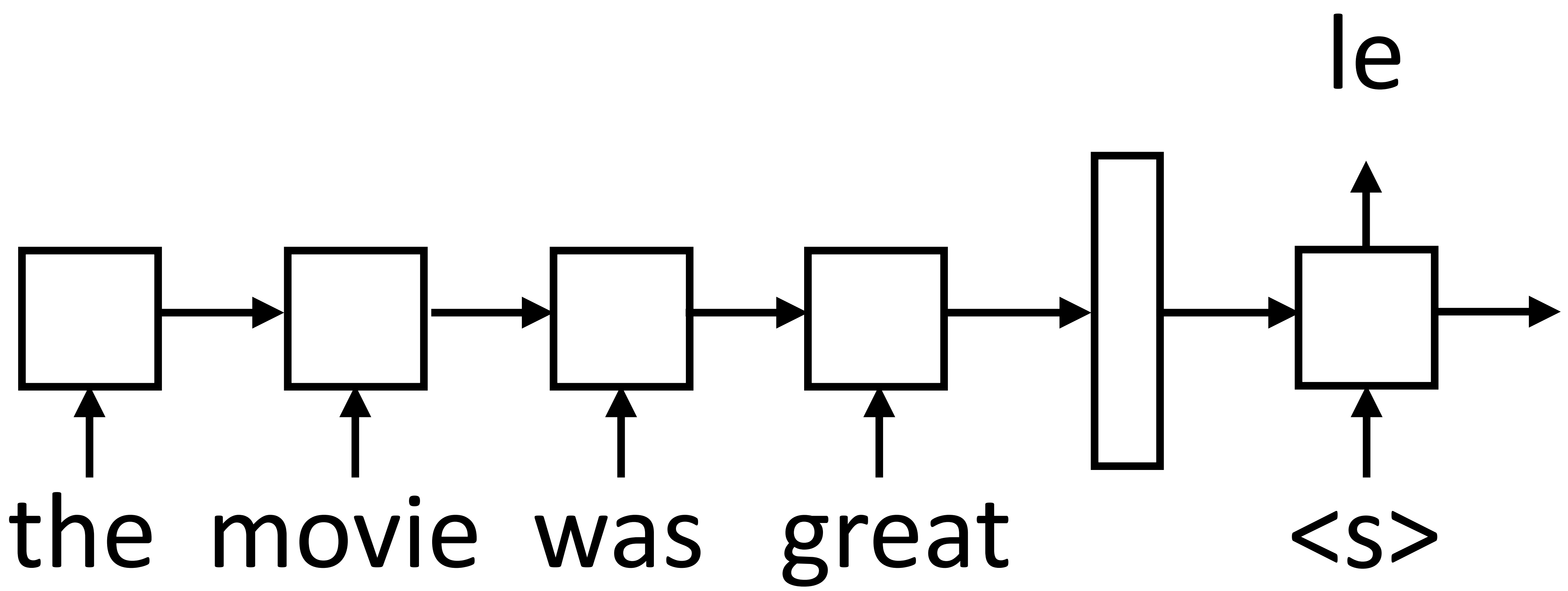
Inference

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



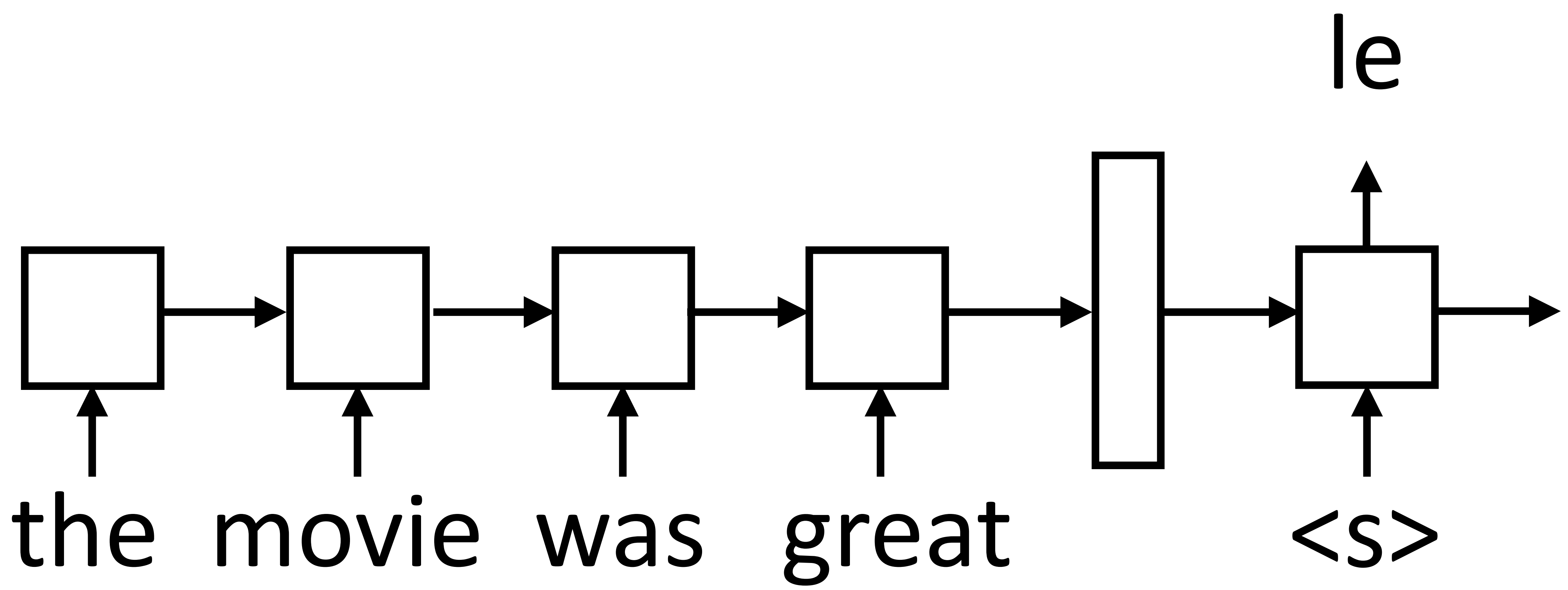
Inference

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



Inference

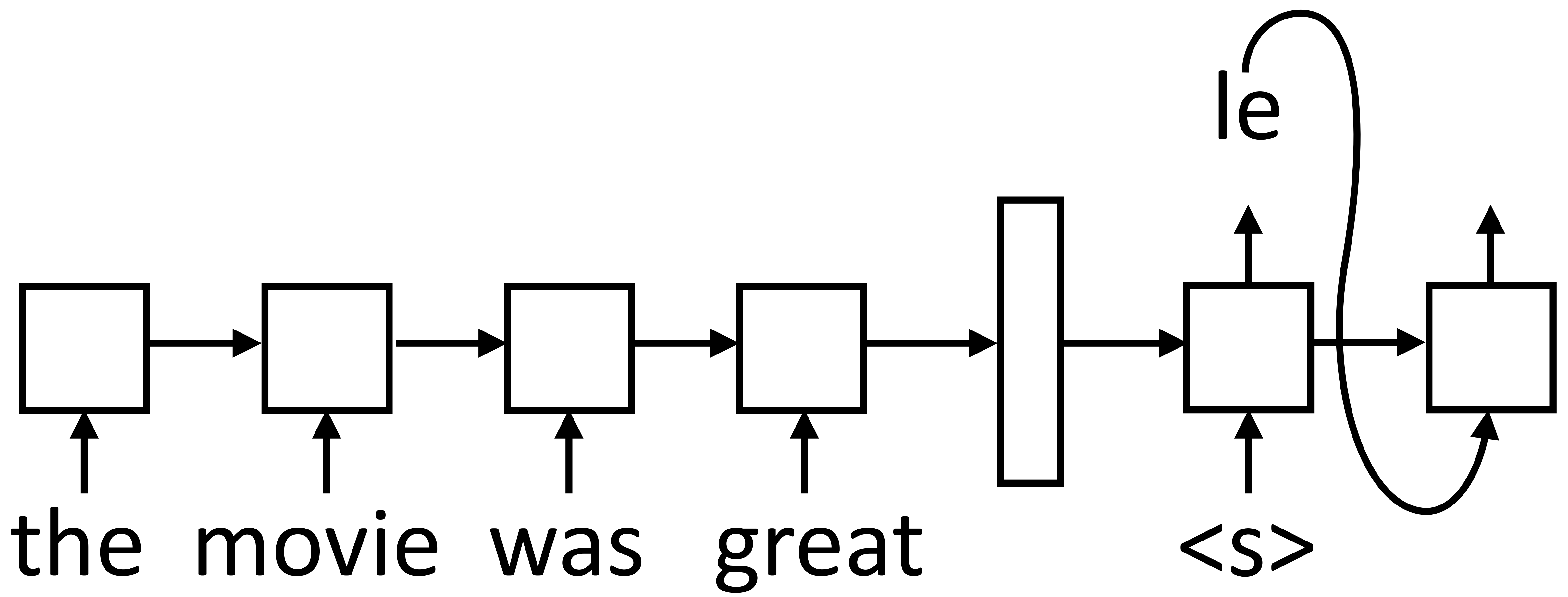
- Generate next word conditioned on previous word as well as hidden state



- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state

Inference

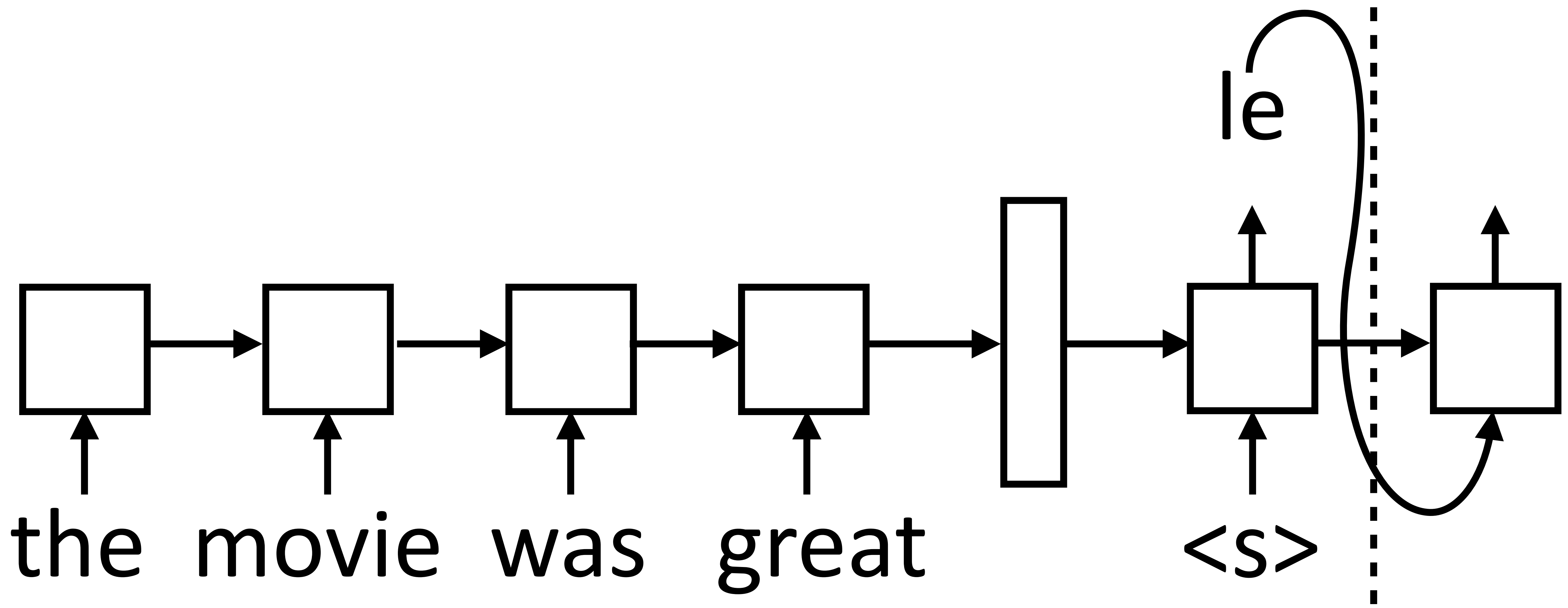
- Generate next word conditioned on previous word as well as hidden state



- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state

Inference

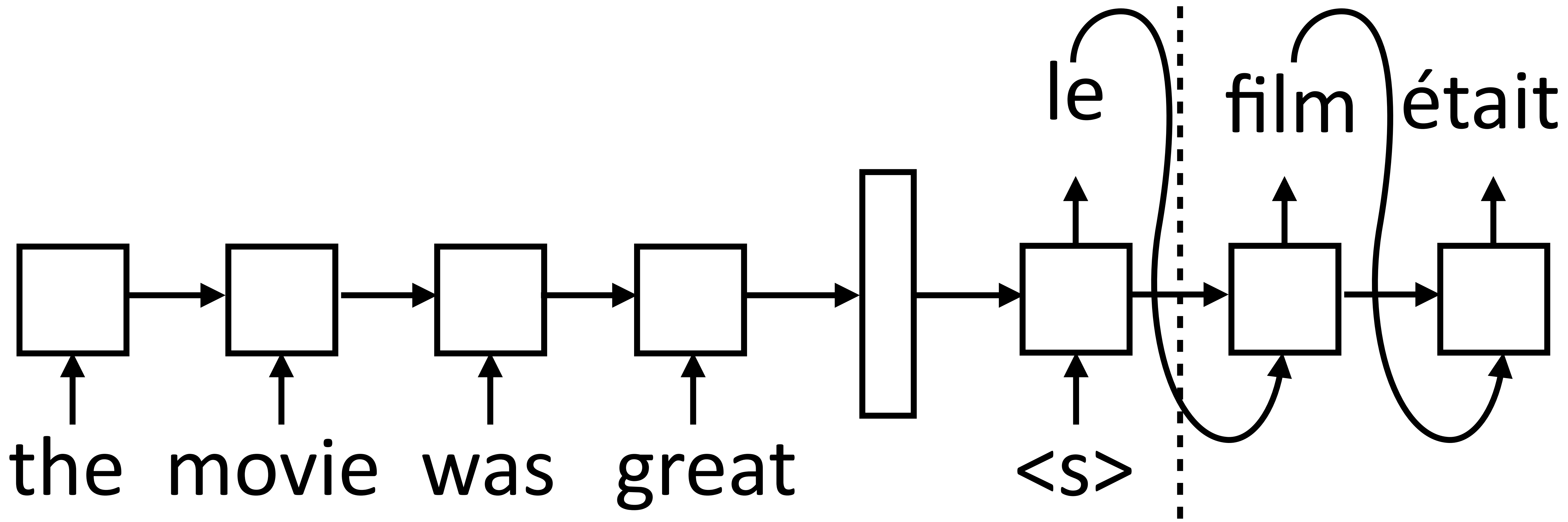
- Generate next word conditioned on previous word as well as hidden state



- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state

Inference

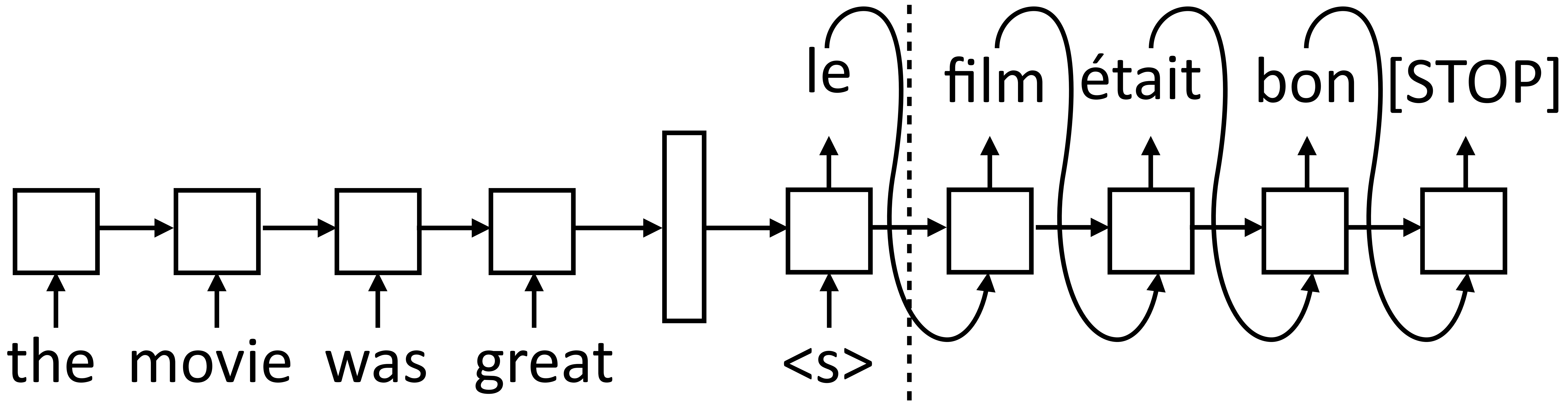
- Generate next word conditioned on previous word as well as hidden state



- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state

Inference

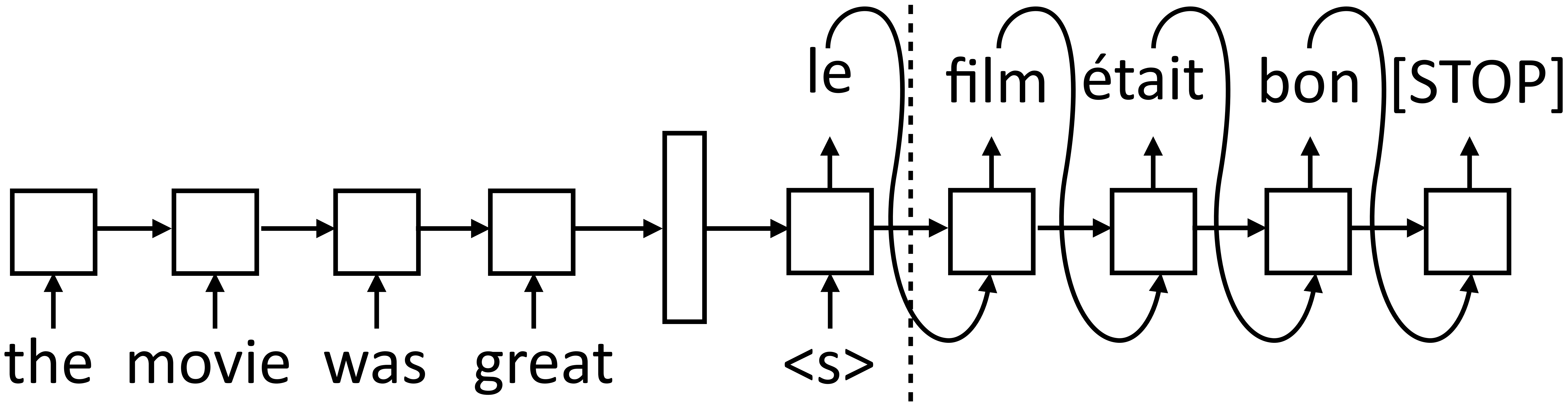
- Generate next word conditioned on previous word as well as hidden state



- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state

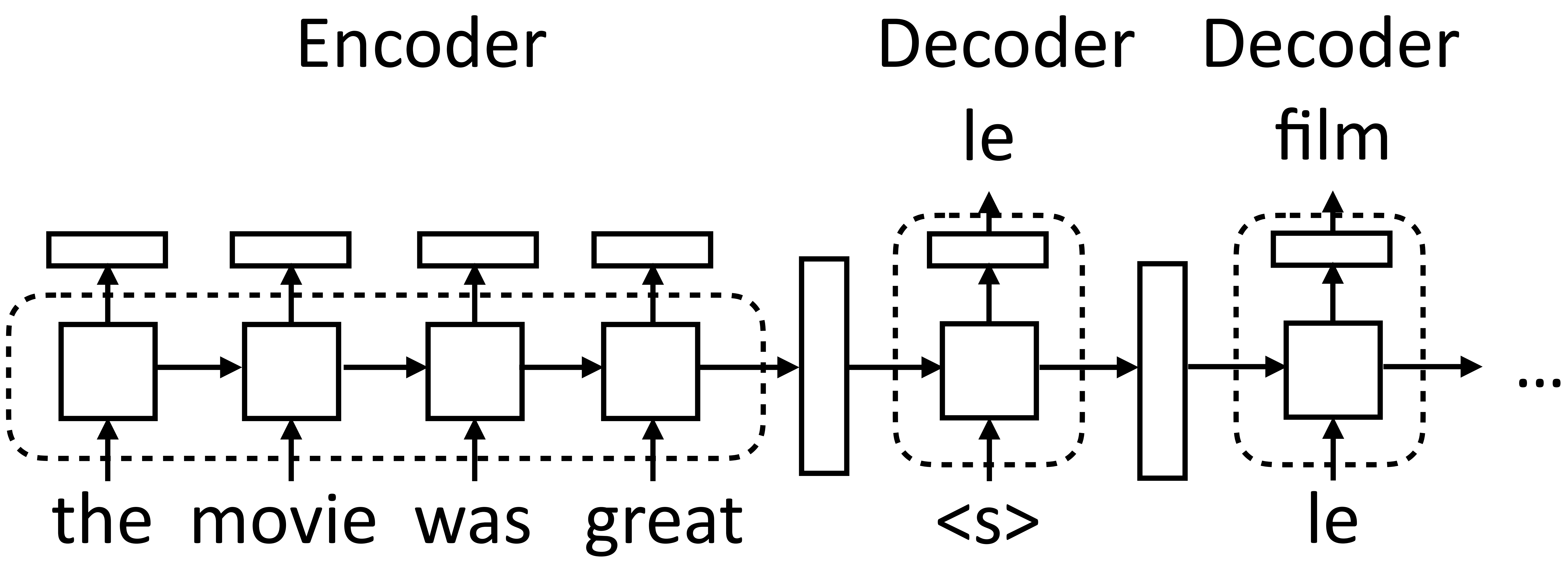
Inference

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

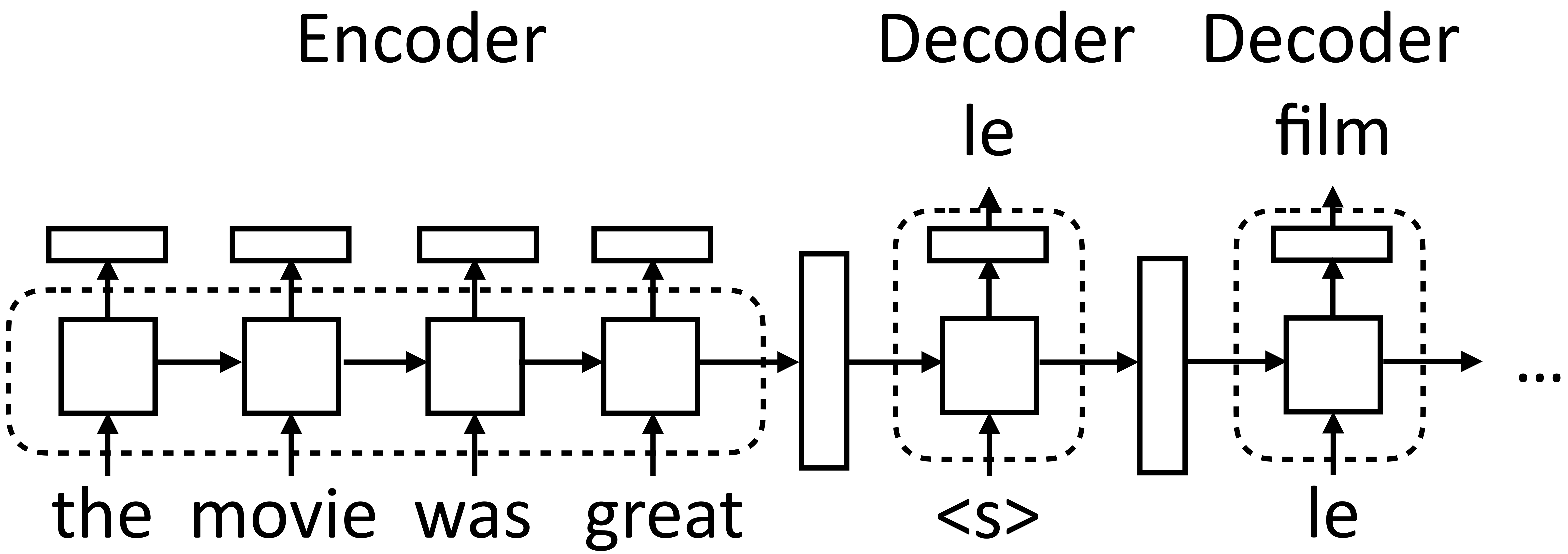


- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models

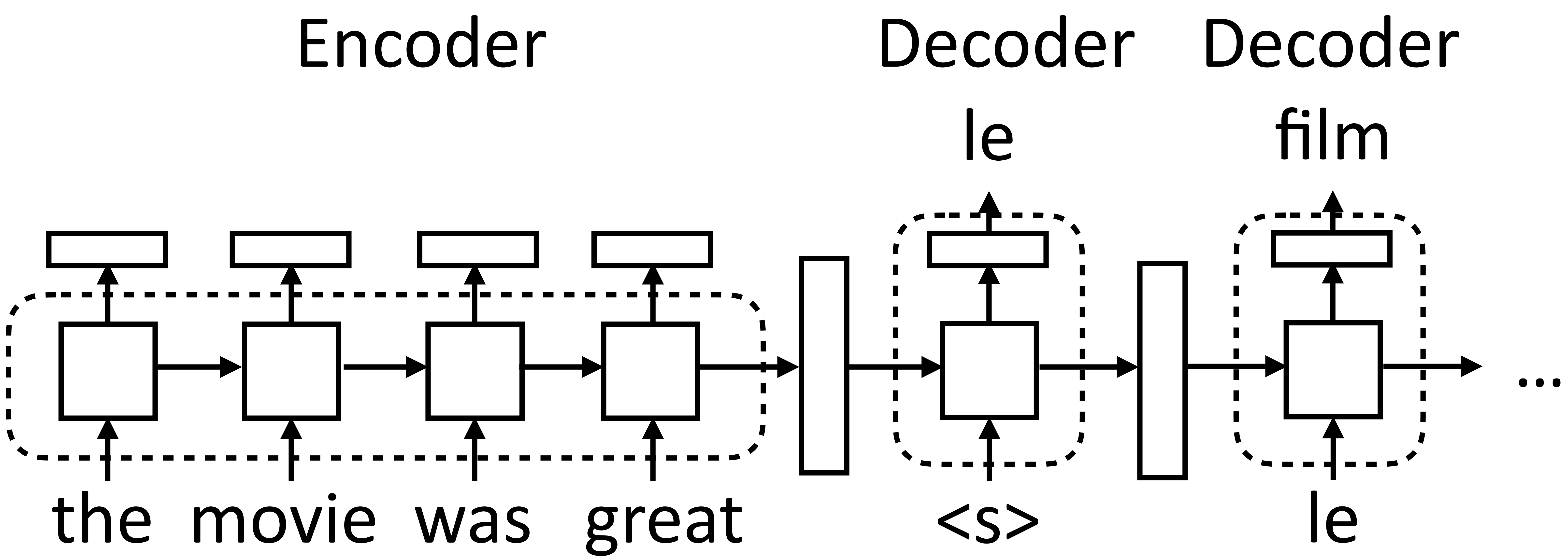


Implementing seq2seq Models



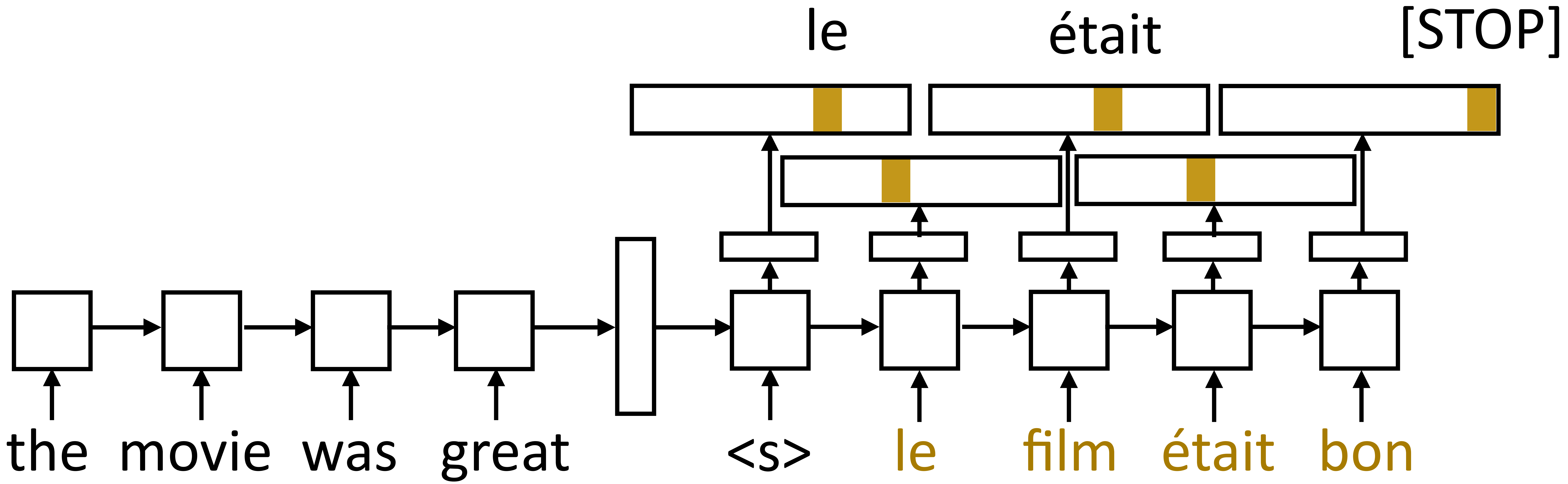
- Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks

Implementing seq2seq Models



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

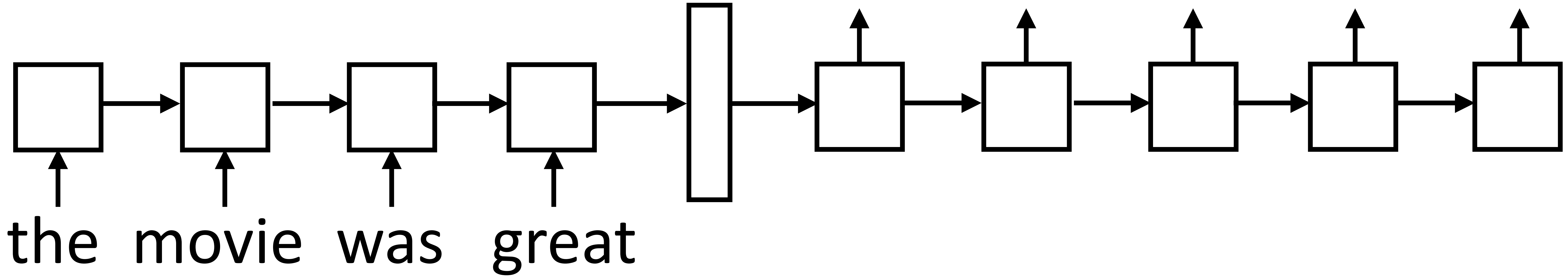
Training



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

Training: Scheduled Sampling

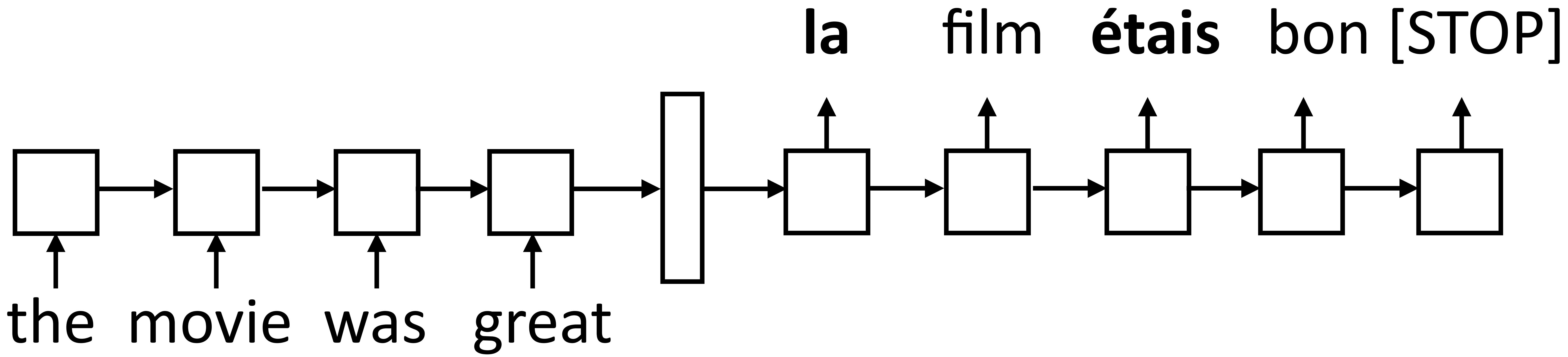
- Model needs to do the right thing even with its own predictions



Bengio et al. (2015)

Training: Scheduled Sampling

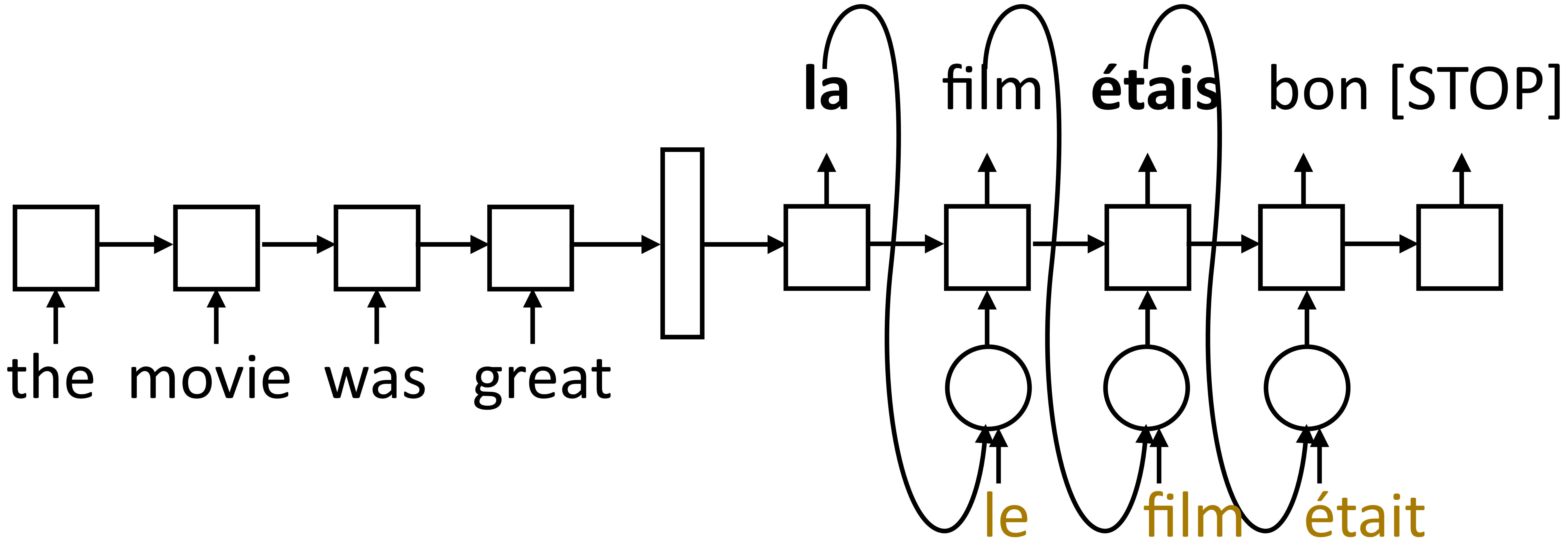
- Model needs to do the right thing even with its own predictions



Bengio et al. (2015)

Training: Scheduled Sampling

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

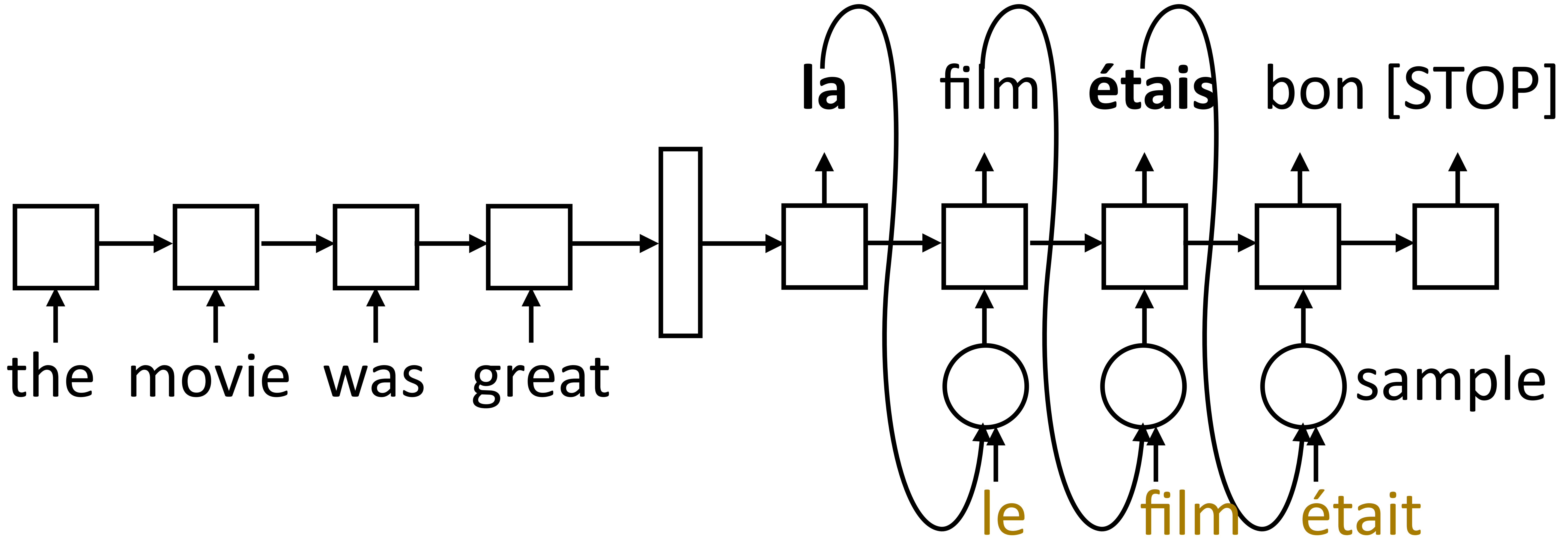


- Scheduled sampling: with probability *p*, take the gold as input, else take the model's prediction

Bengio et al. (2015)

Training: Scheduled Sampling

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



- Scheduled sampling: with probability *p*, take the gold as input, else take the model's prediction
- Starting with *p* = 1 and decaying it works best

Bengio et al. (2015)

Implementation Details

Implementation Details

- Sentence lengths vary for both encoder and decoder:

Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length

Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length
- Encoder: Can be a CNN/LSTM/…

Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length

- 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

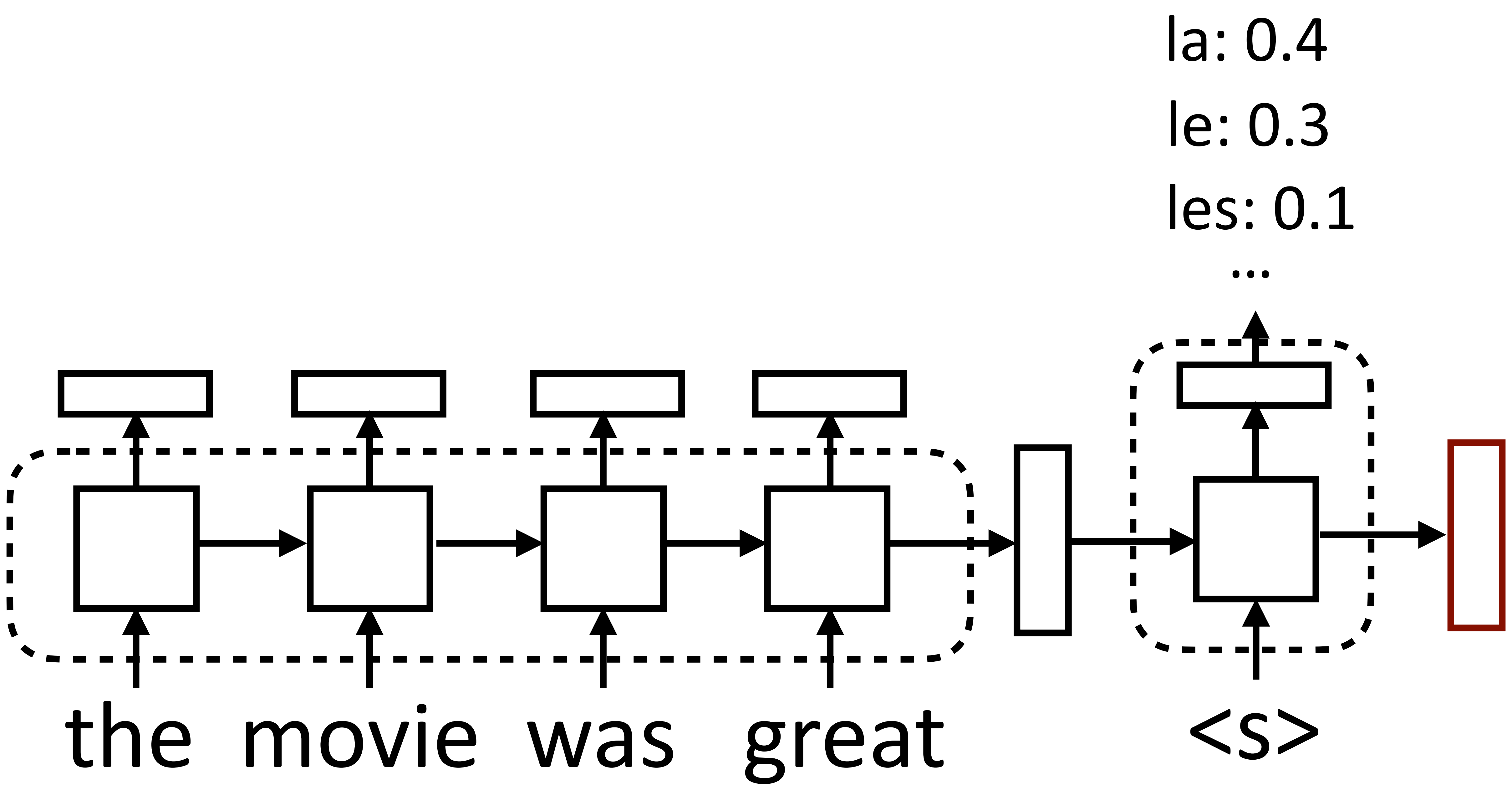
Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length
- 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:

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

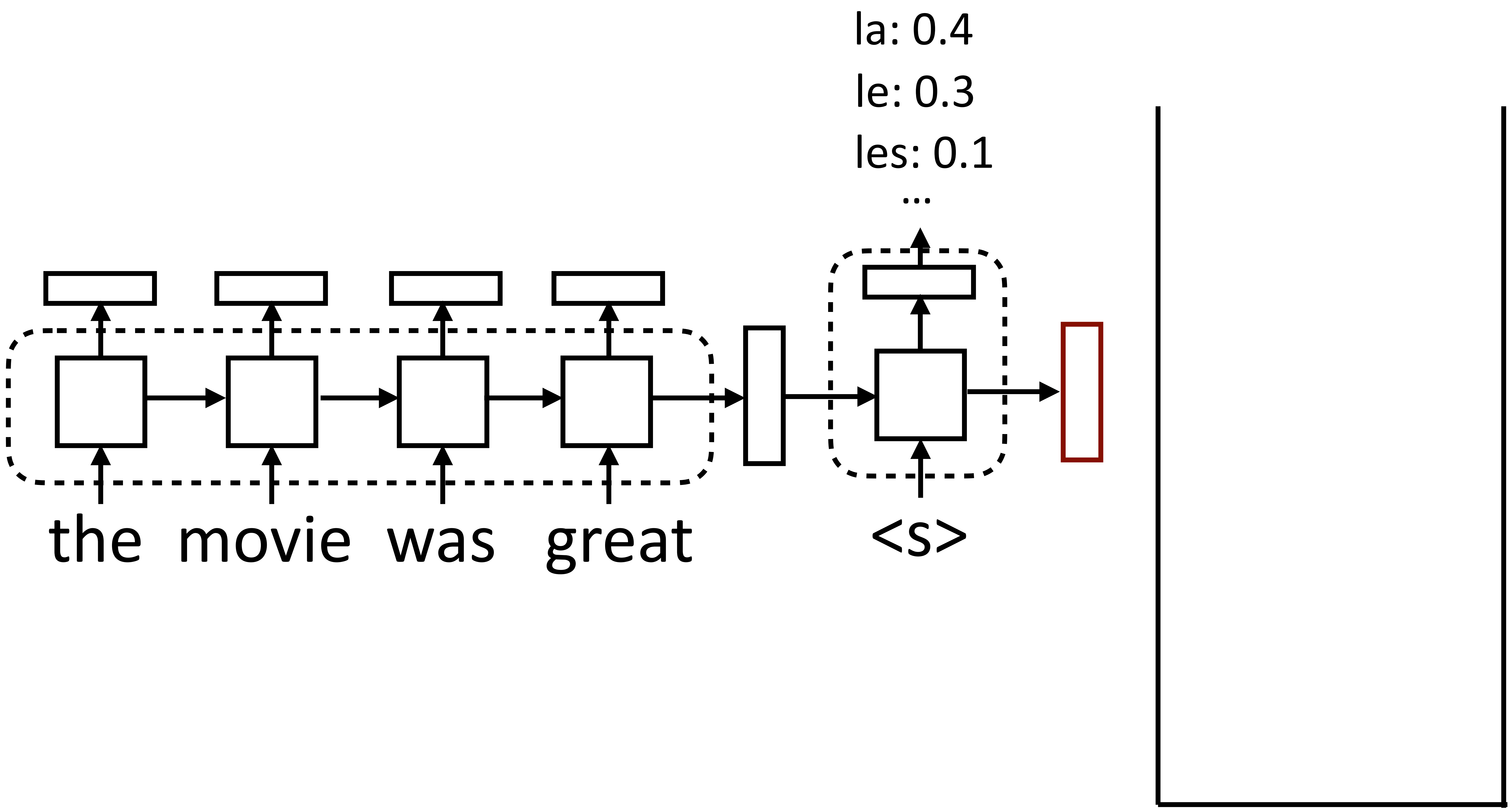
Beam Search

- Maintain decoder state, token history in beam



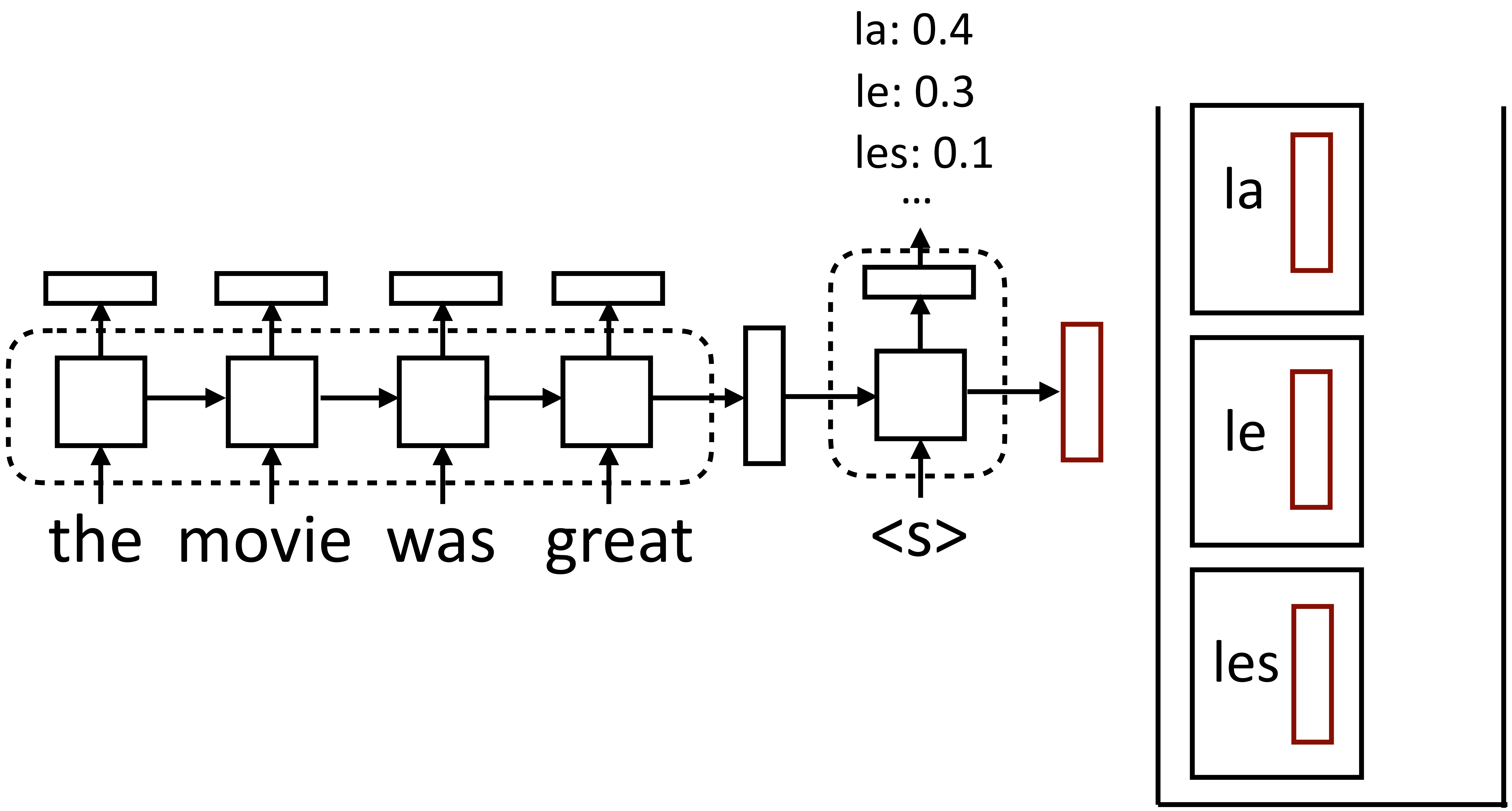
Beam Search

- Maintain decoder state, token history in beam



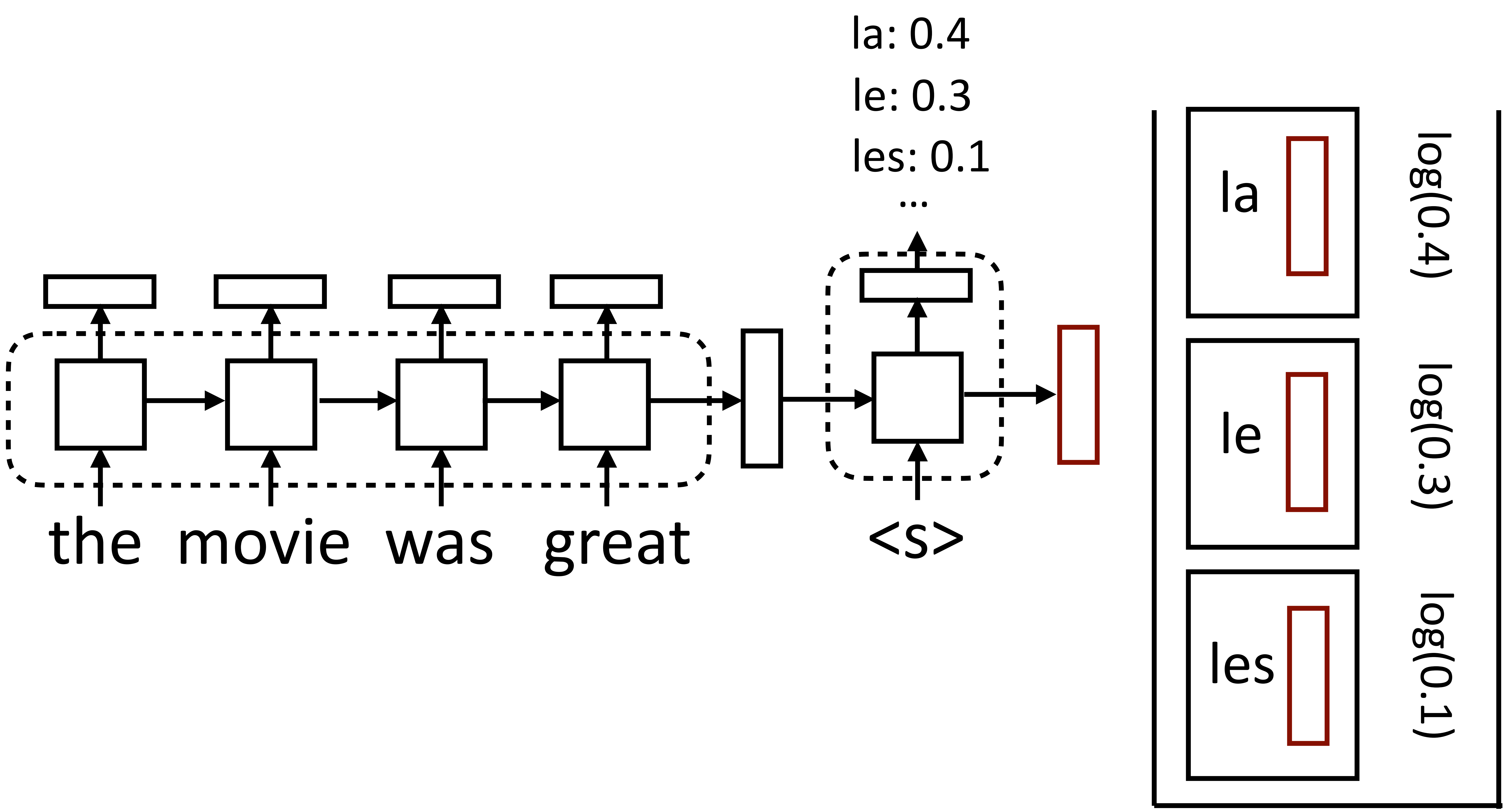
Beam Search

- Maintain decoder state, token history in beam



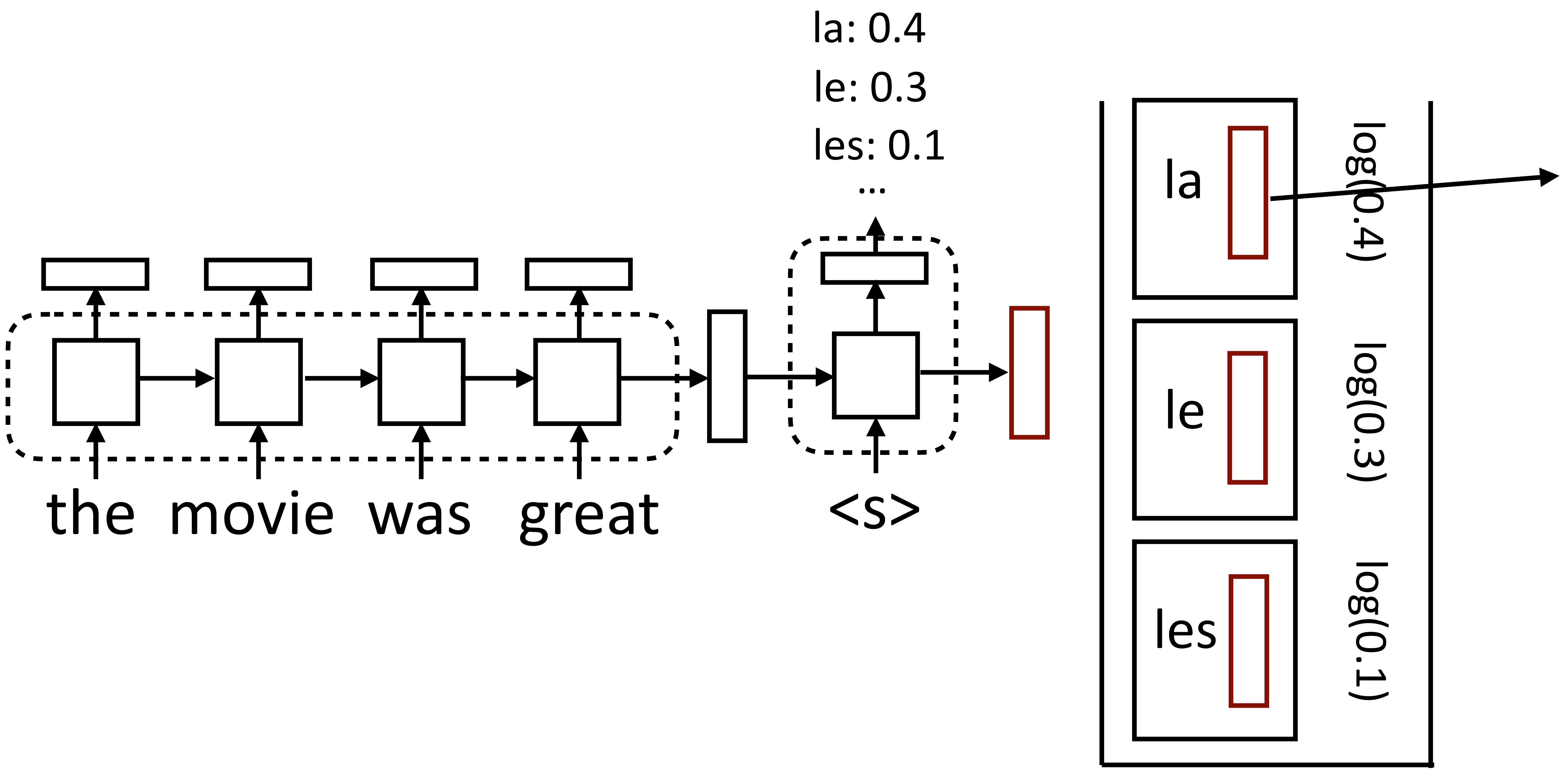
Beam Search

- Maintain decoder state, token history in beam



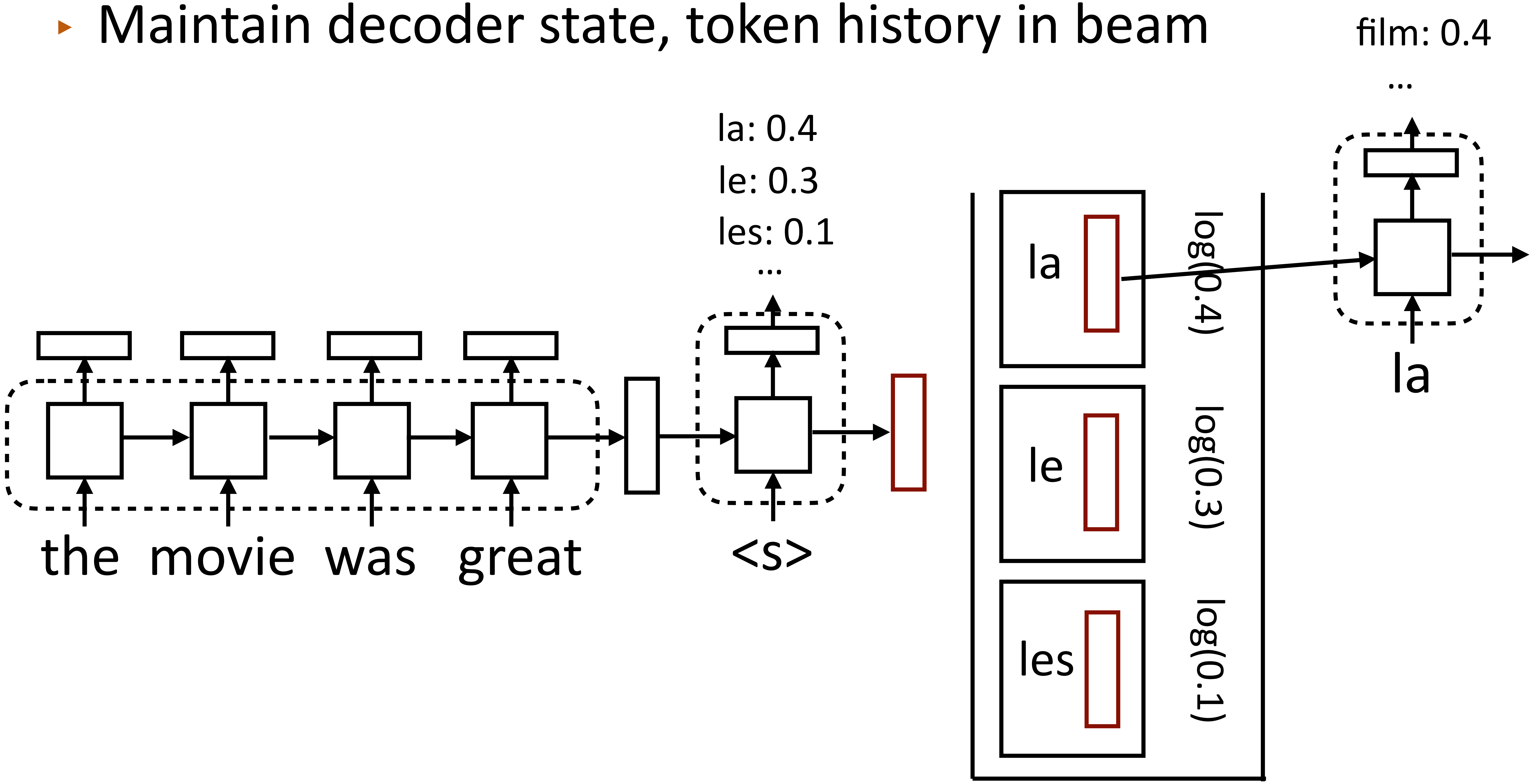
Beam Search

- Maintain decoder state, token history in beam



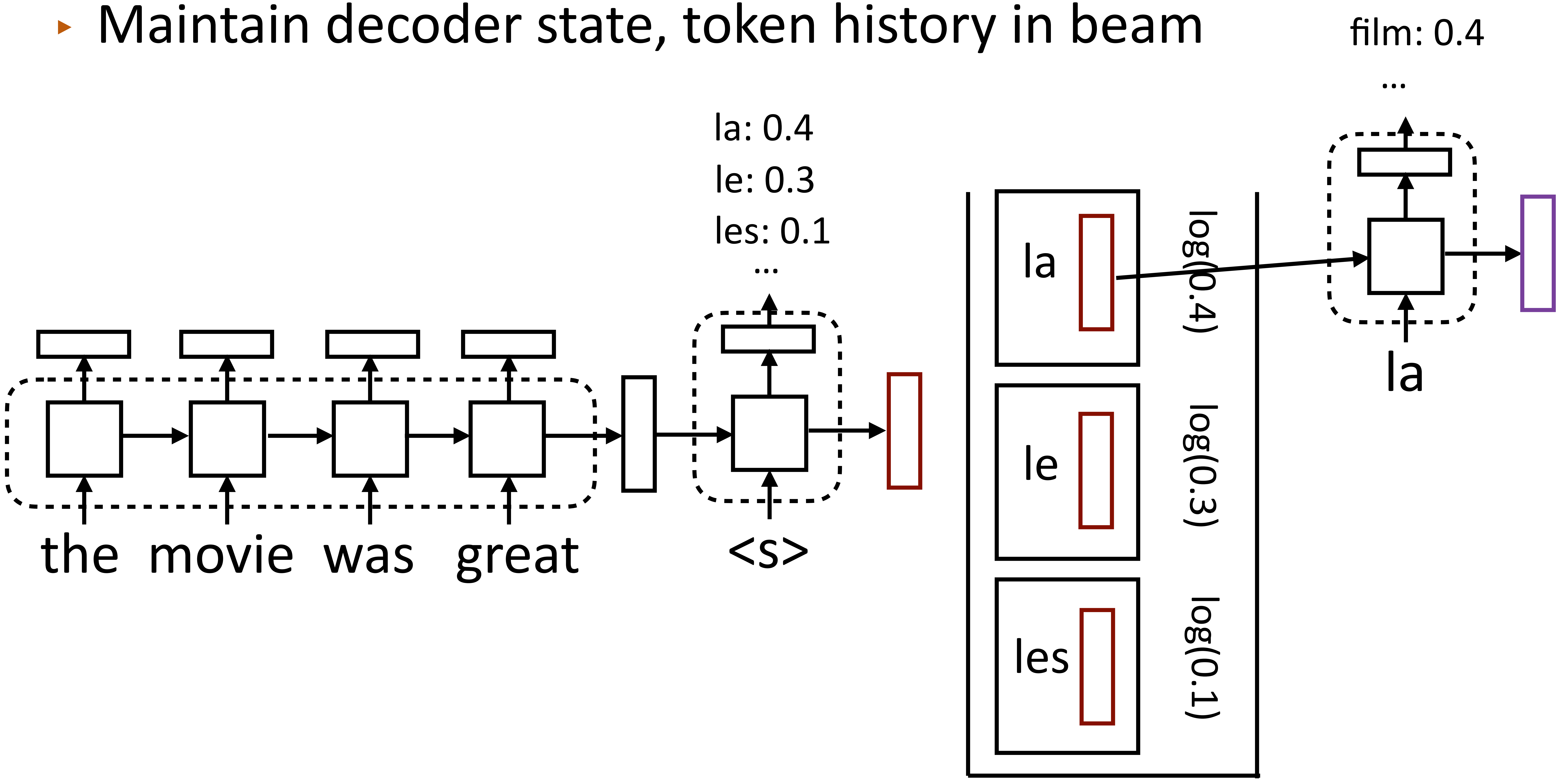
Beam Search

- Maintain decoder state, token history in beam



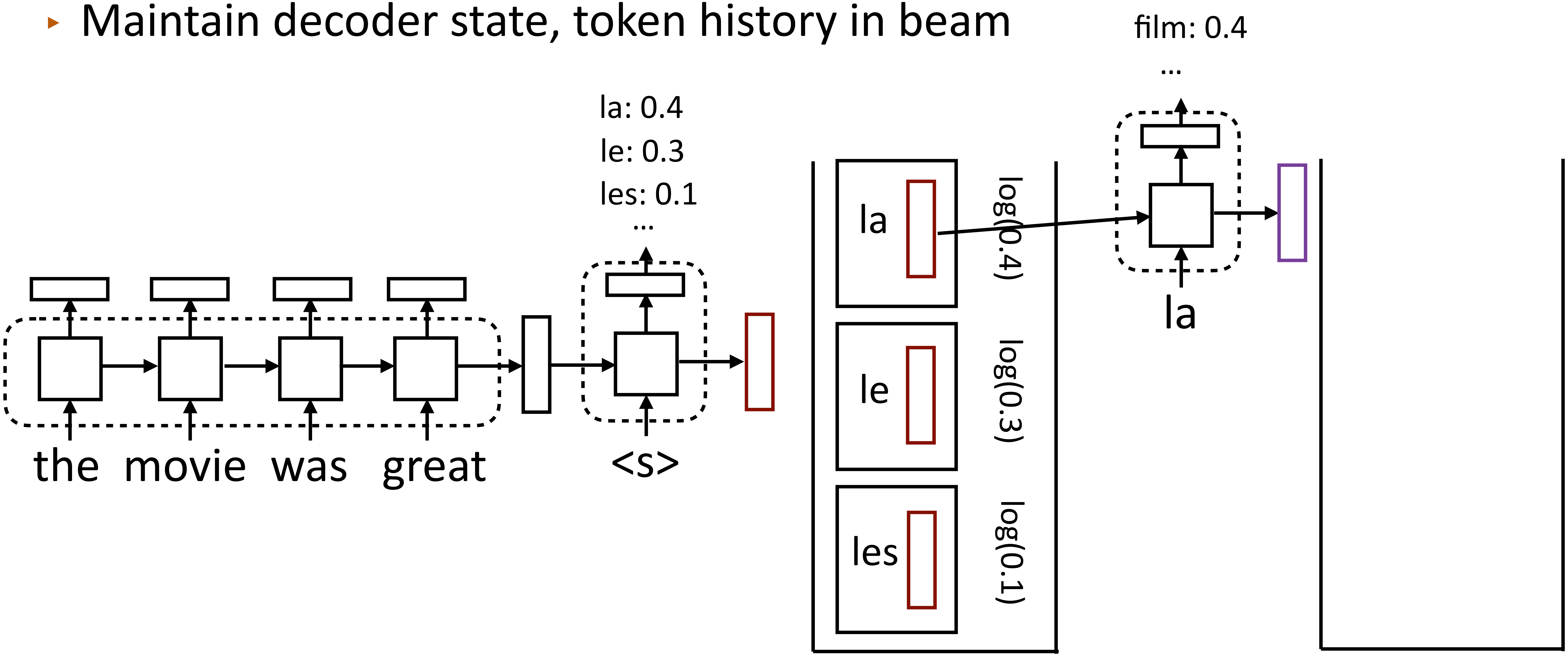
Beam Search

- Maintain decoder state, token history in beam



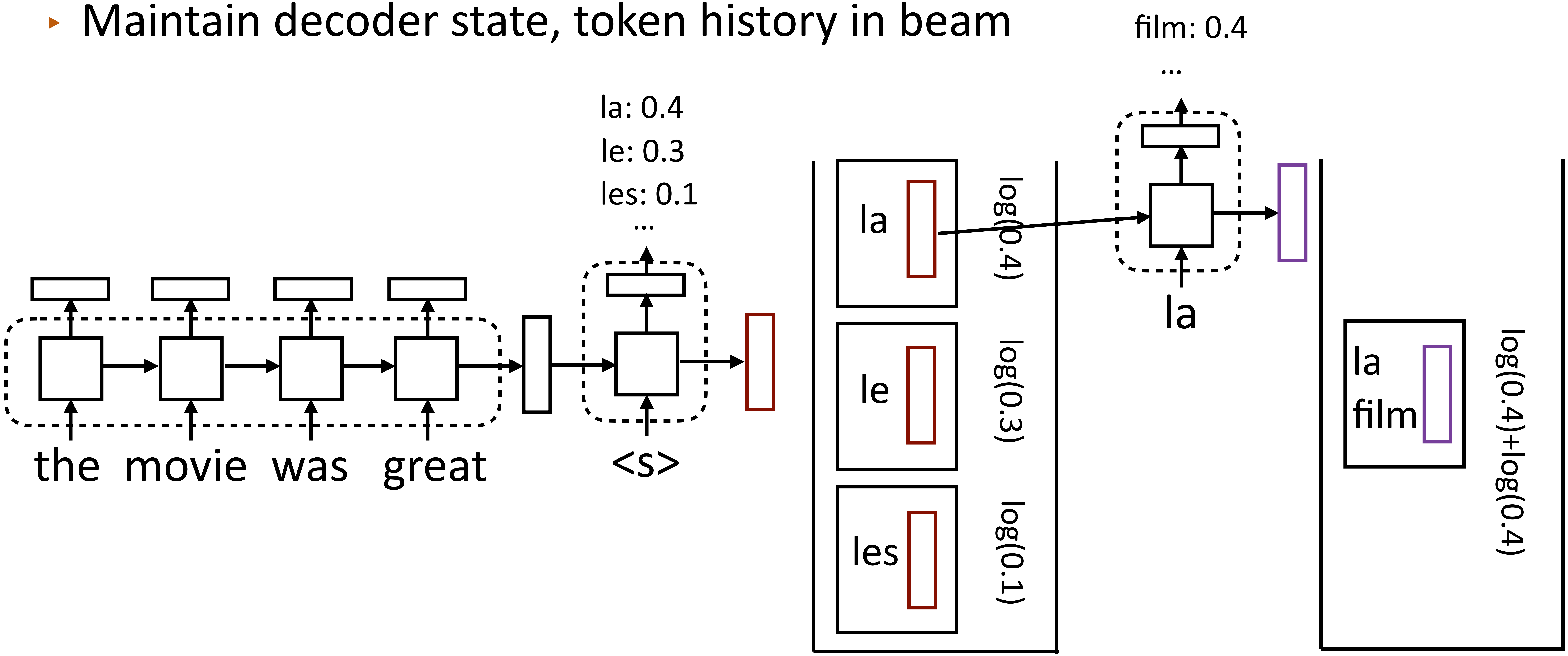
Beam Search

- Maintain decoder state, token history in beam



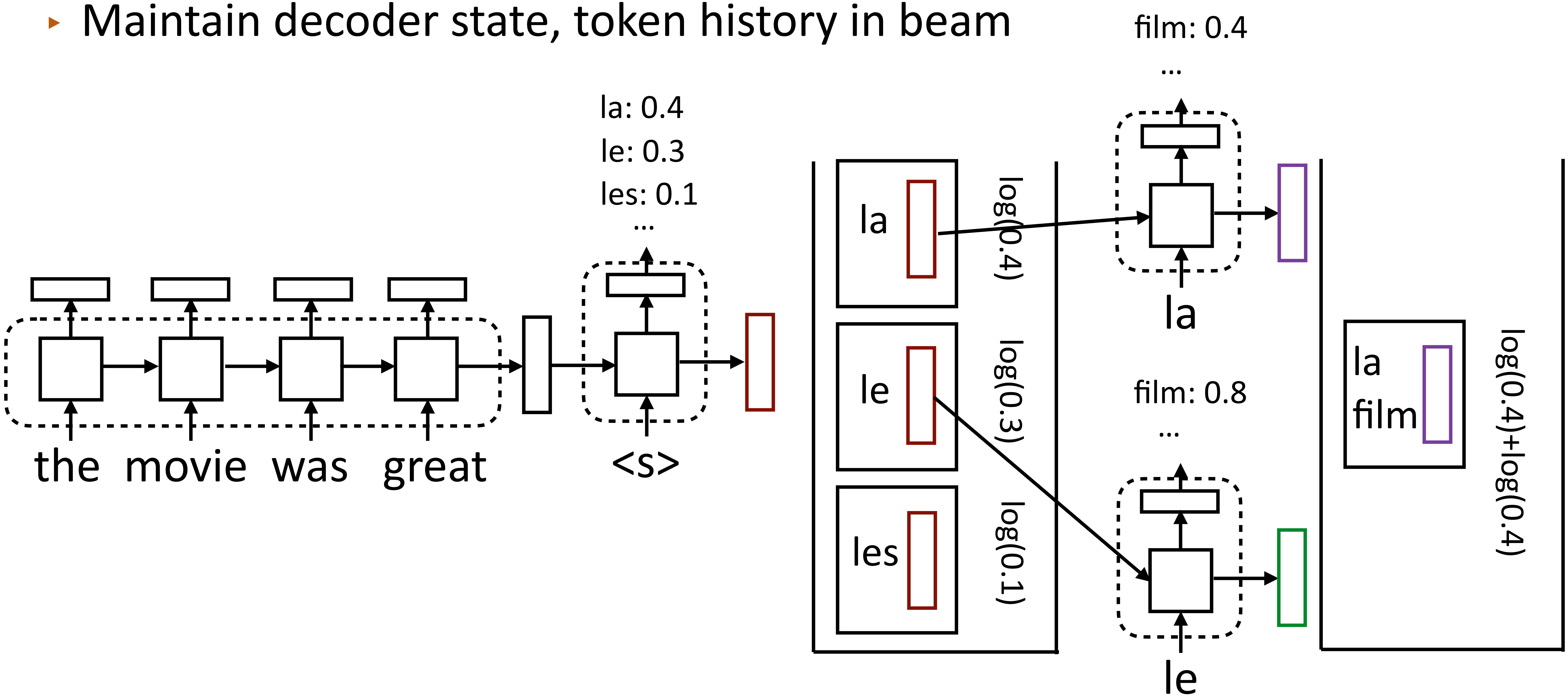
Beam Search

- Maintain decoder state, token history in beam



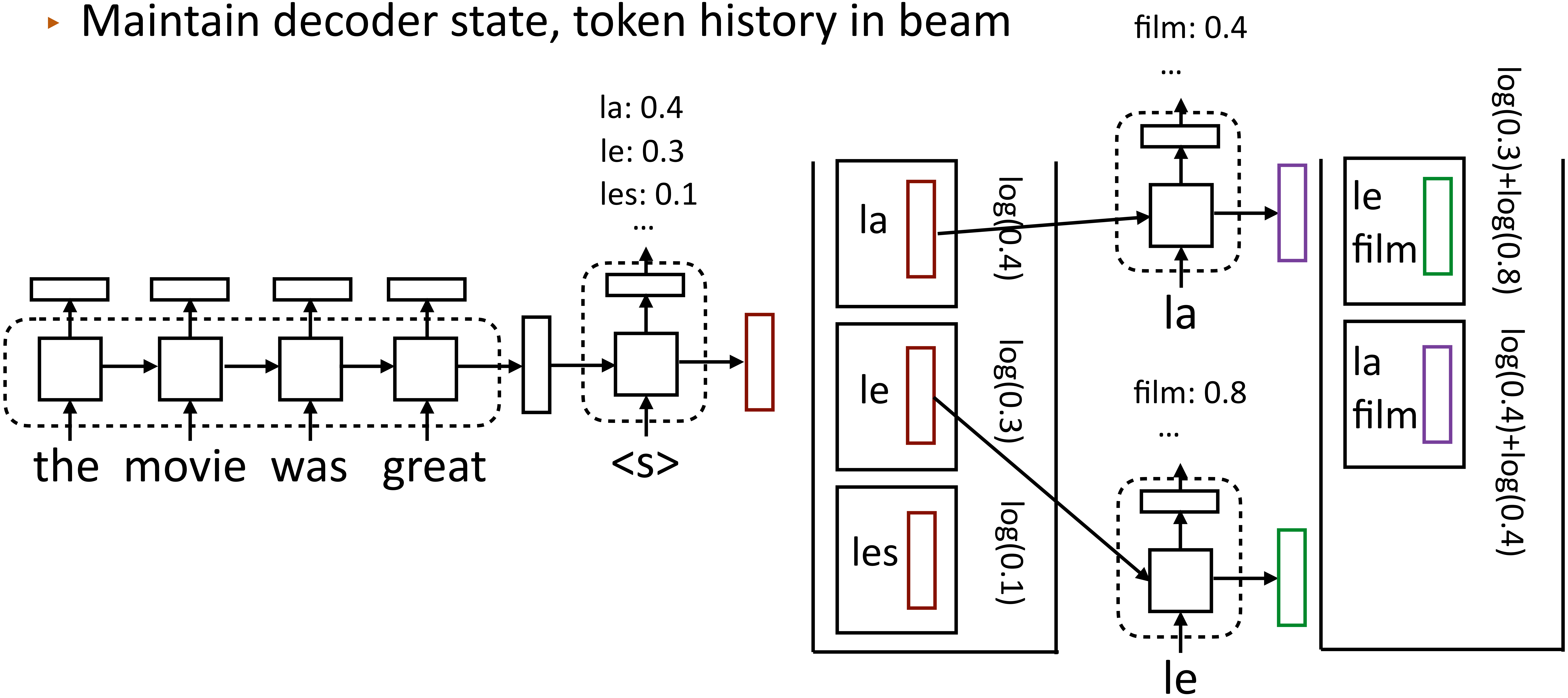
Beam Search

- Maintain decoder state, token history in beam



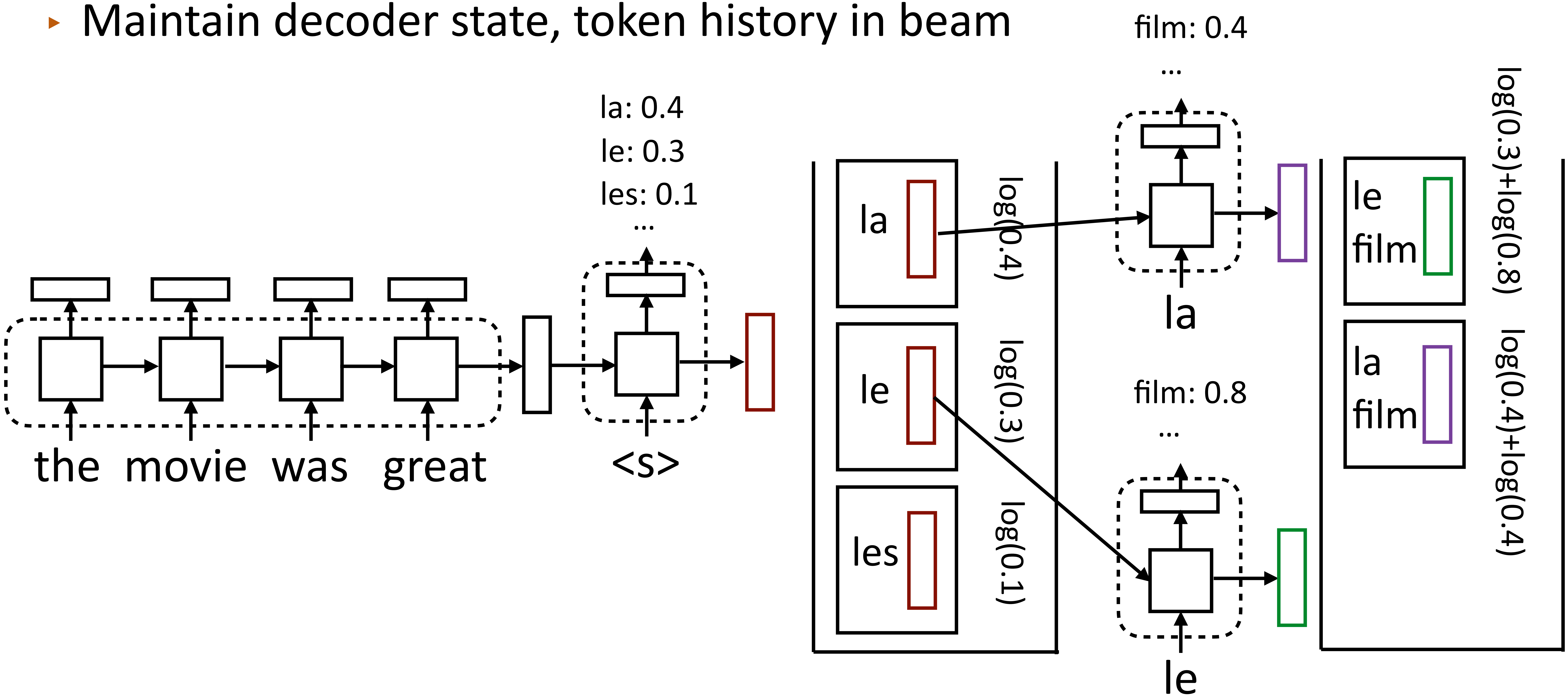
Beam Search

- Maintain decoder state, token history in beam



Beam Search

- Maintain decoder state, token history in beam



- 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)

Semantic Parsing as Translation

"what states border Texas"

↓

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

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

Jia and Liang (2015)

Semantic Parsing as Translation

"what states border Texas"

↓

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

- 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

Jia and Liang (2015)

Semantic Parsing as Translation

"what states border Texas"

↓

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

- 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)

Regex Prediction

- Can use for other semantic parsing-like tasks

Locascio et al. (2016)

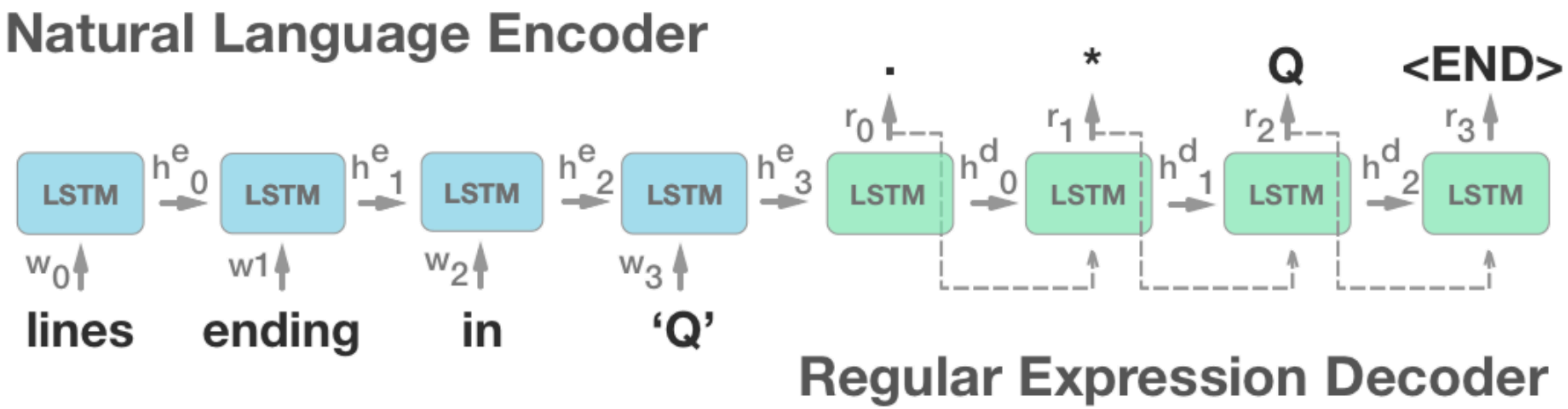
Regex Prediction

- Can use for other semantic parsing-like tasks
- Predict regex from text

Locascio et al. (2016)

Regex Prediction

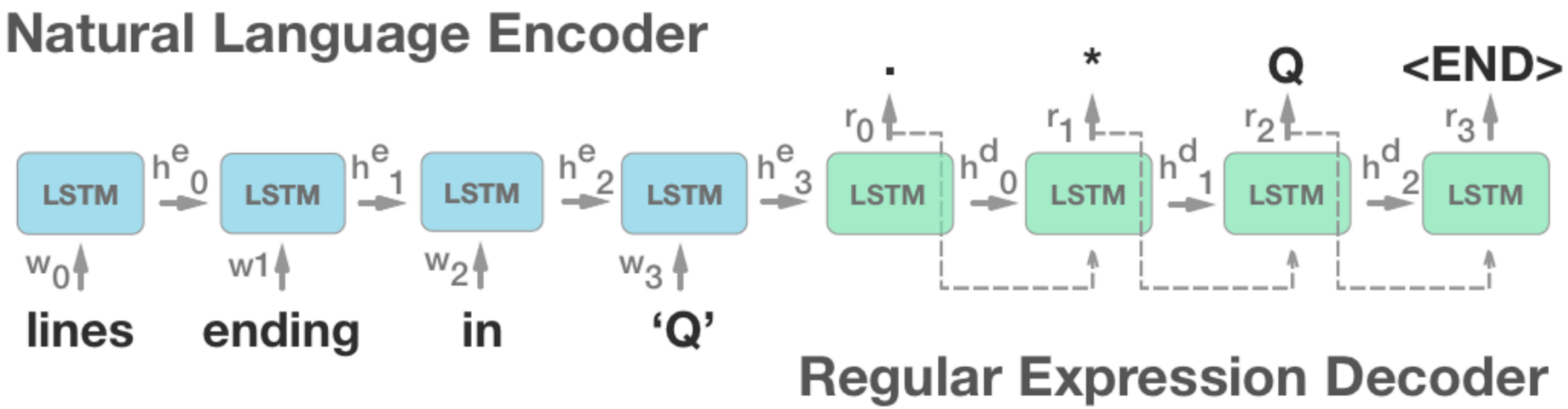
- Can use for other semantic parsing-like tasks
- Predict regex from text



Locascio et al. (2016)

Regex Prediction

- Can use for other semantic parsing-like tasks
- Predict regex from text



- 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:

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

Zhong et al. (2017)

SQL Generation

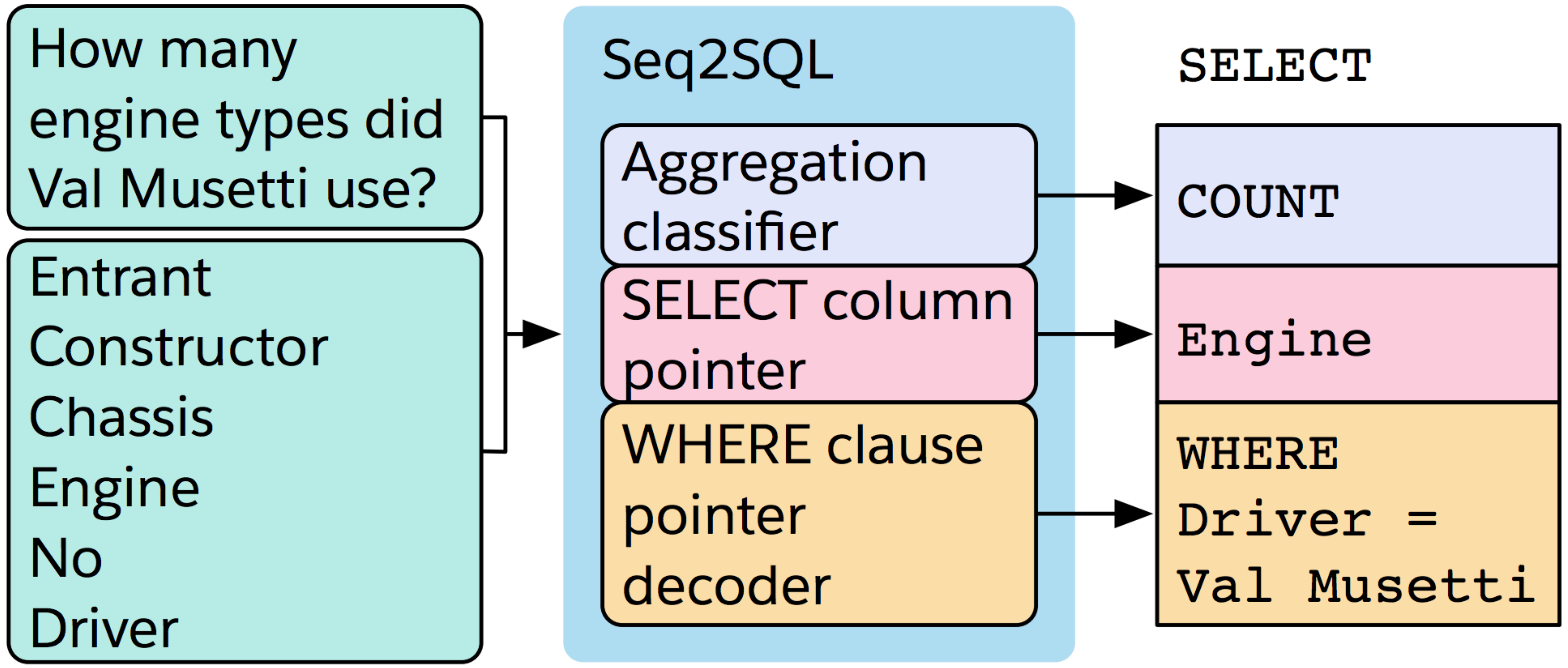
- Convert natural language description into a SQL query against some DB

Question:

How many CFL teams are from York College?

SQL:

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



Zhong et al. (2017)

SQL Generation

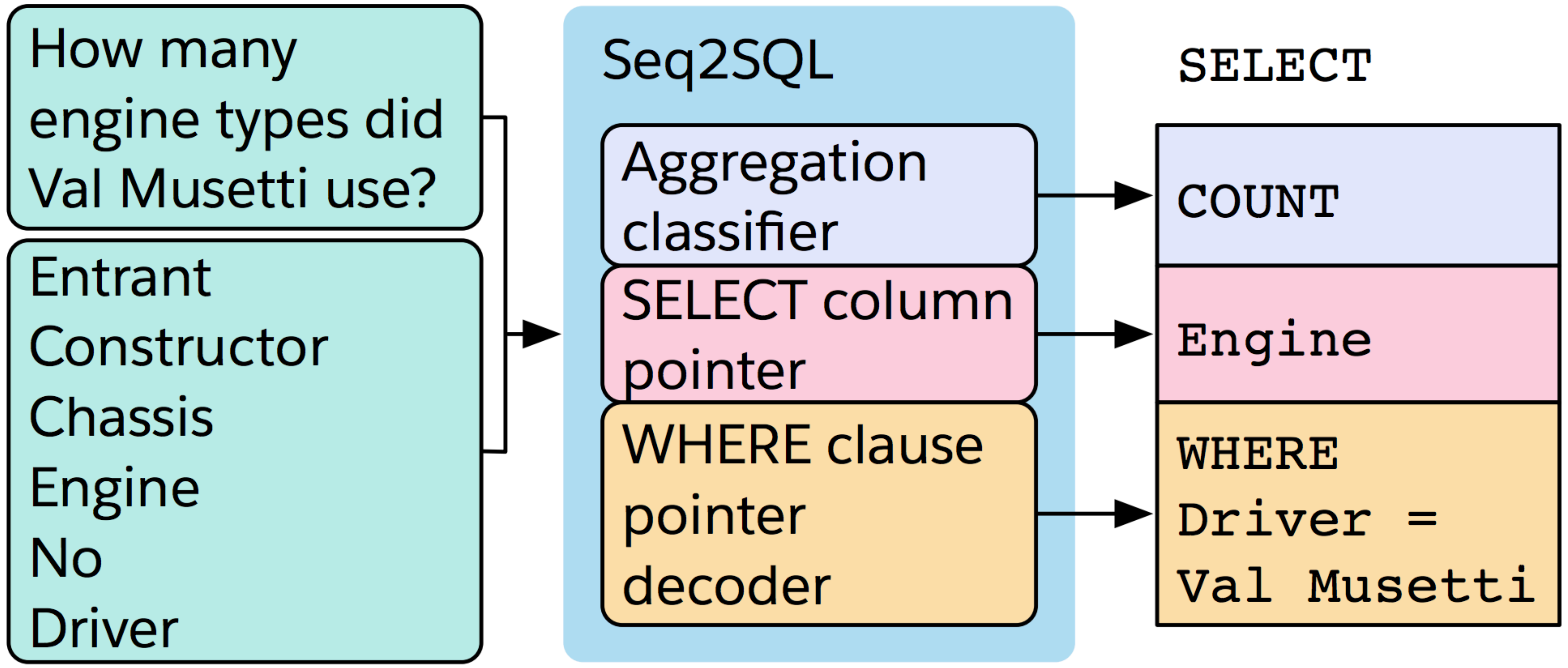
- Convert natural language description into a SQL query against some DB
- How to ensure that well-formed SQL is generated?

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

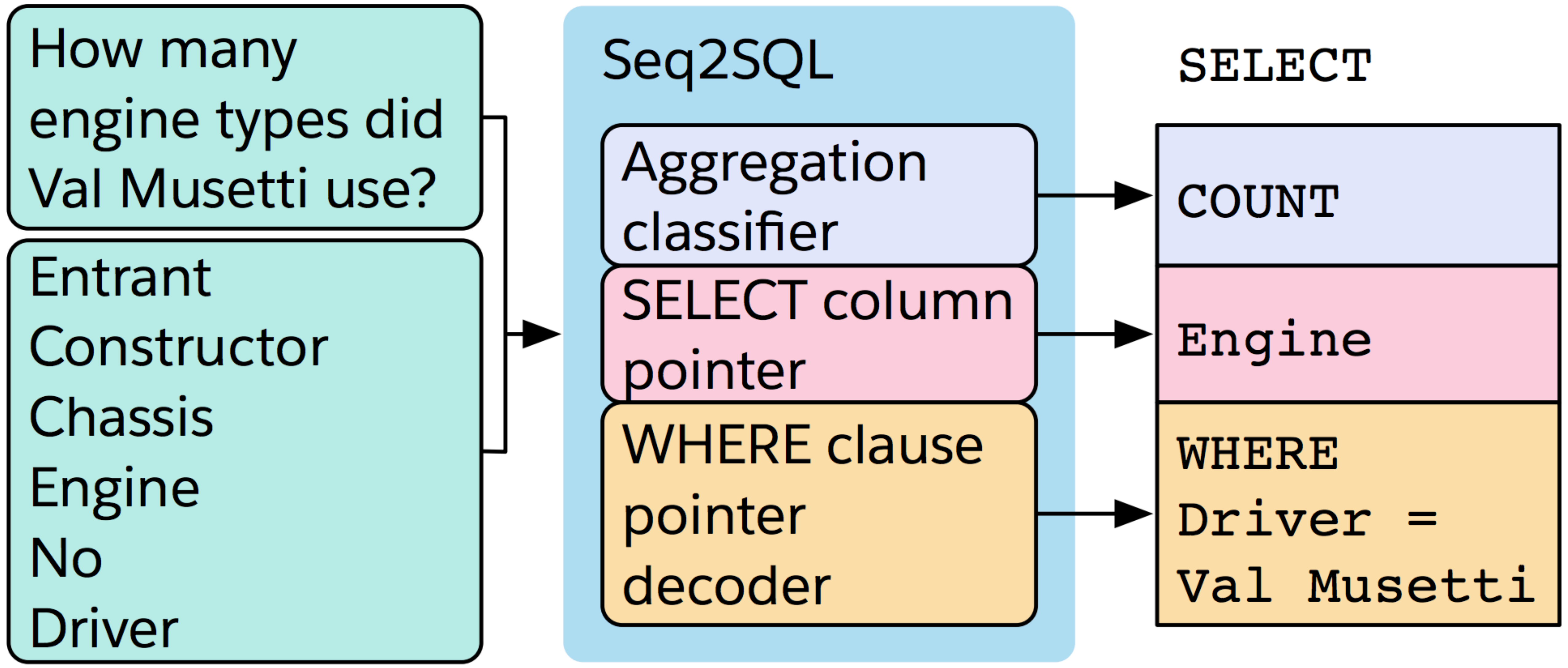
- Convert natural language description into a SQL query against some DB
- How to ensure that well-formed SQL is generated?
  - Three seq2seq models

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

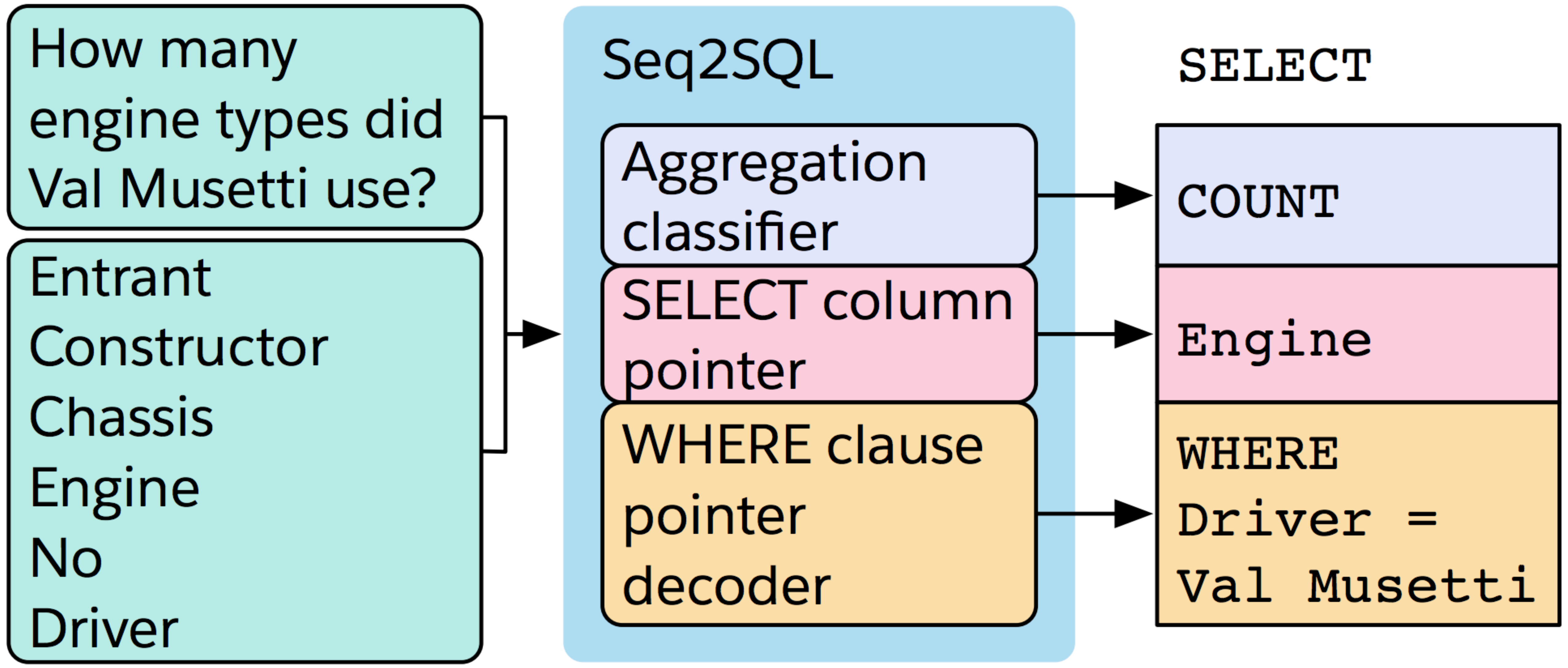
- Convert natural language description into a SQL query against some DB
- How to ensure that well-formed SQL is generated?
  - Three seq2seq models
- How to capture column names + constants?

Question:

How many CFL teams are from York College?

SQL:

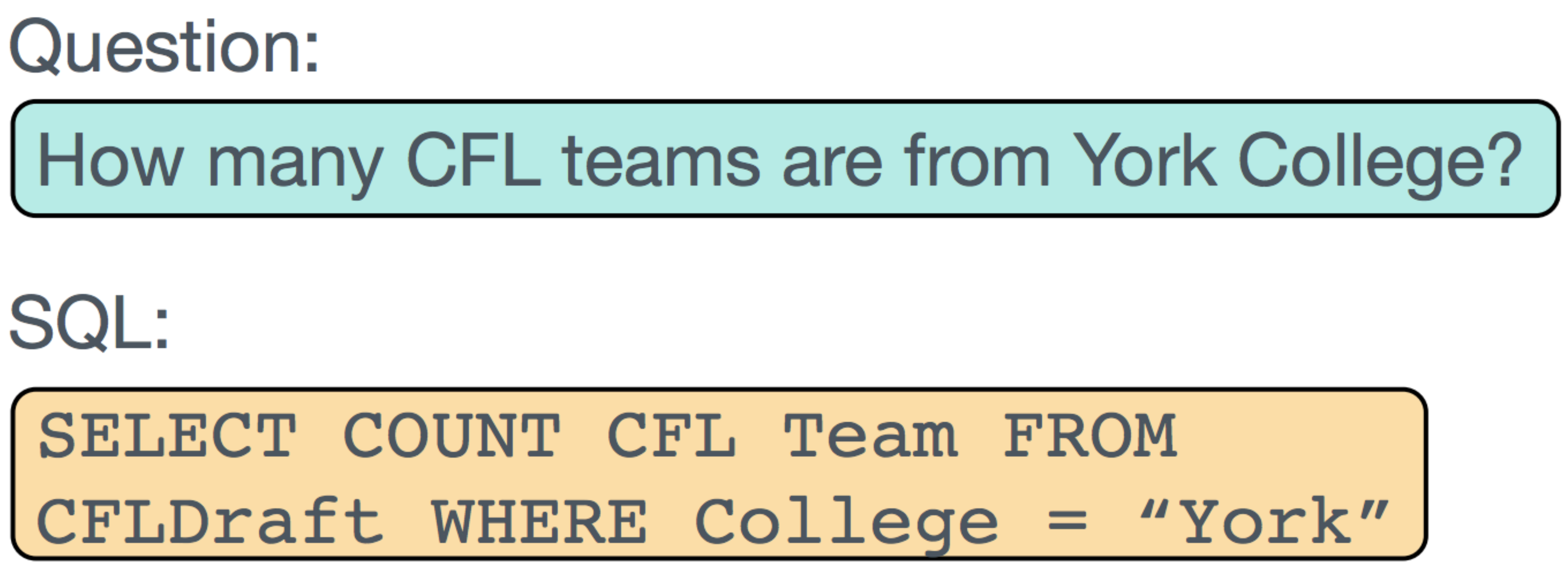
```
SELECT COUNT CFL Team FROM
CFLDraft WHERE College = “York”
```

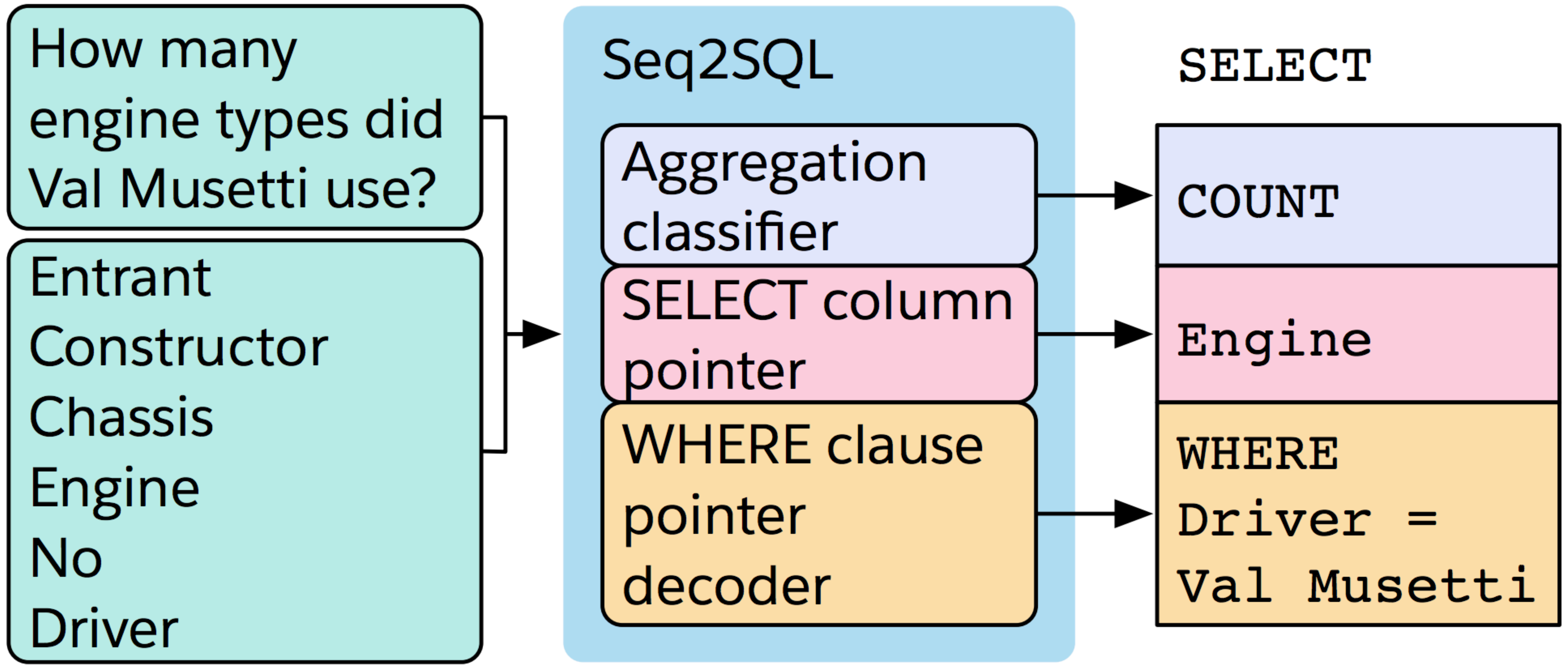


Zhong et al. (2017)

SQL Generation

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





Zhong et al. (2017)

Attention

Problems with Seq2seq Models

- Encoder-decoder models like to repeat themselves:

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**

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

Problems with Seq2seq Models

- Encoder-decoder models like to repeat themselves:

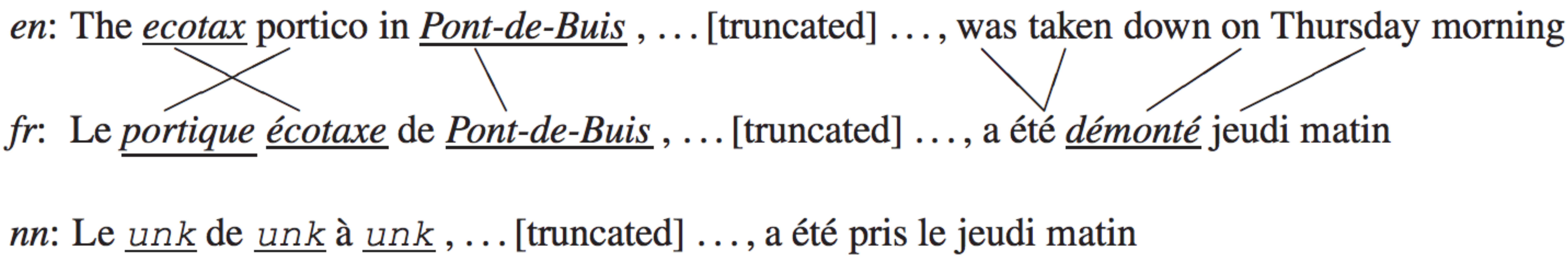
Un garçon joue dans la neige → A boy plays in the snow **boy plays boy plays**

- 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

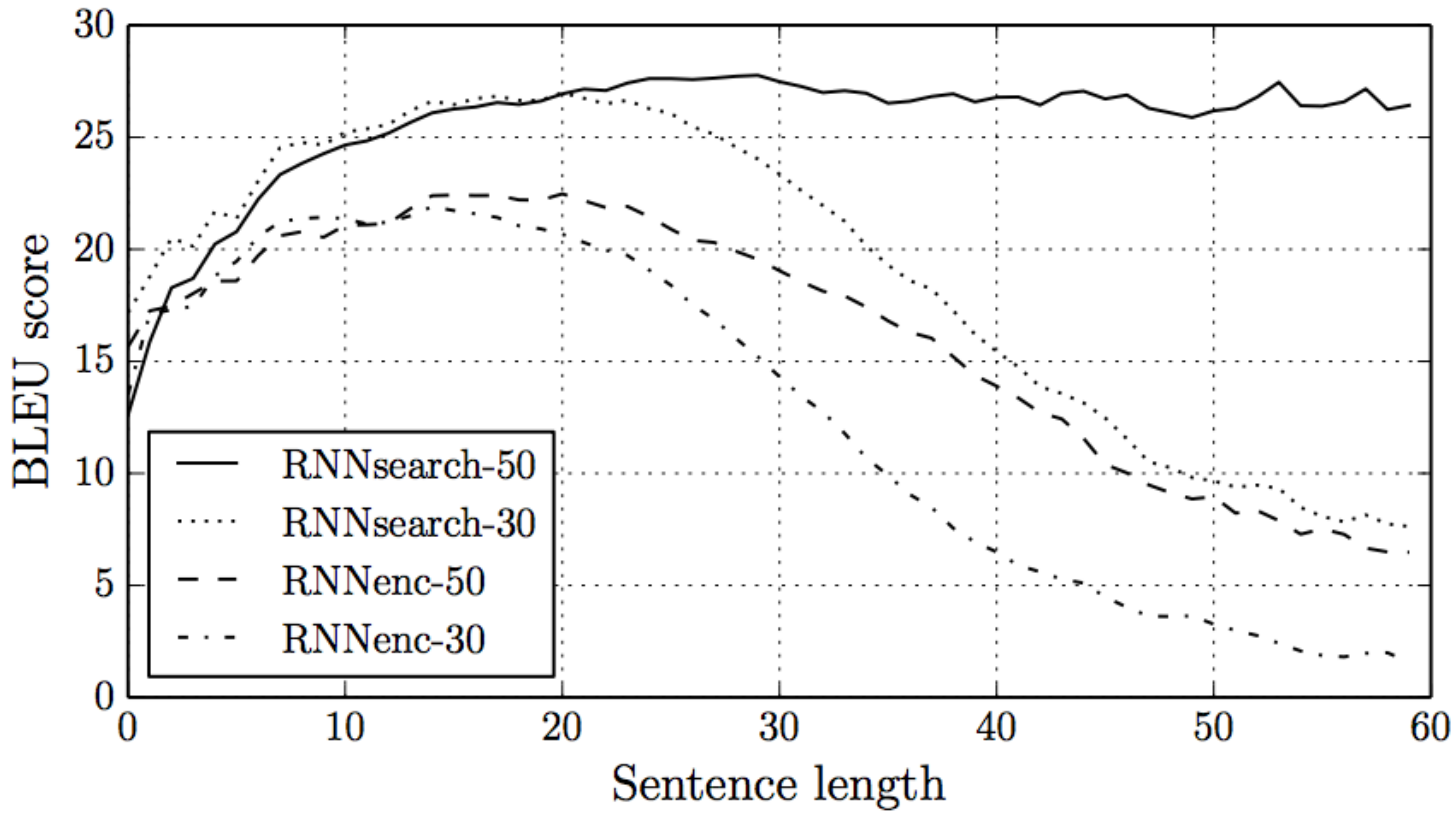
- Unknown words:



- 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

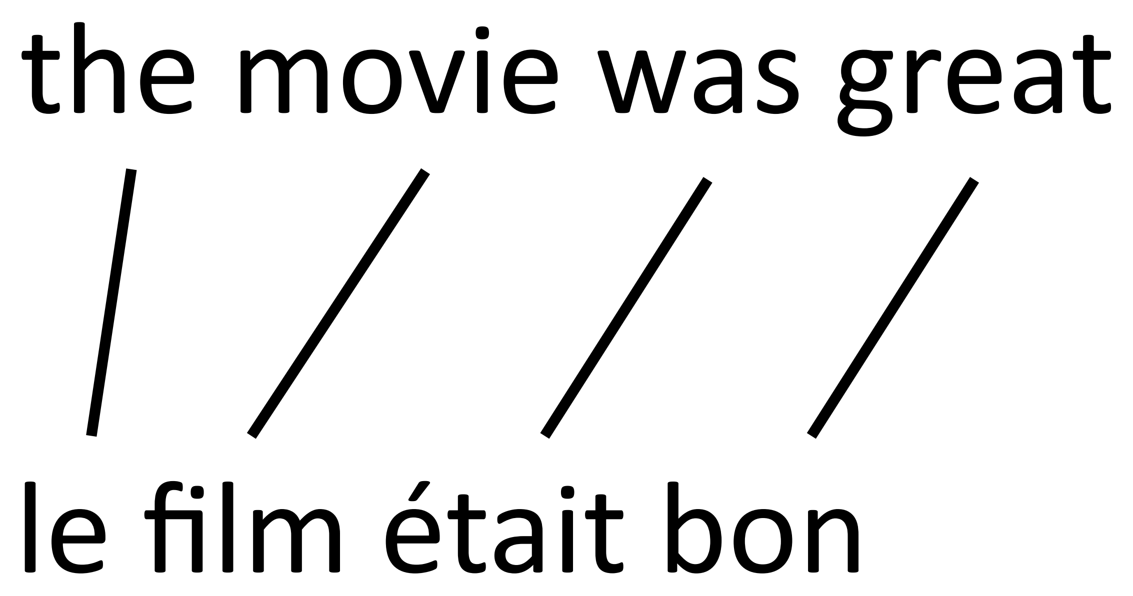
Bahdanau et al. (2014)

Aligned Inputs

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

Aligned Inputs

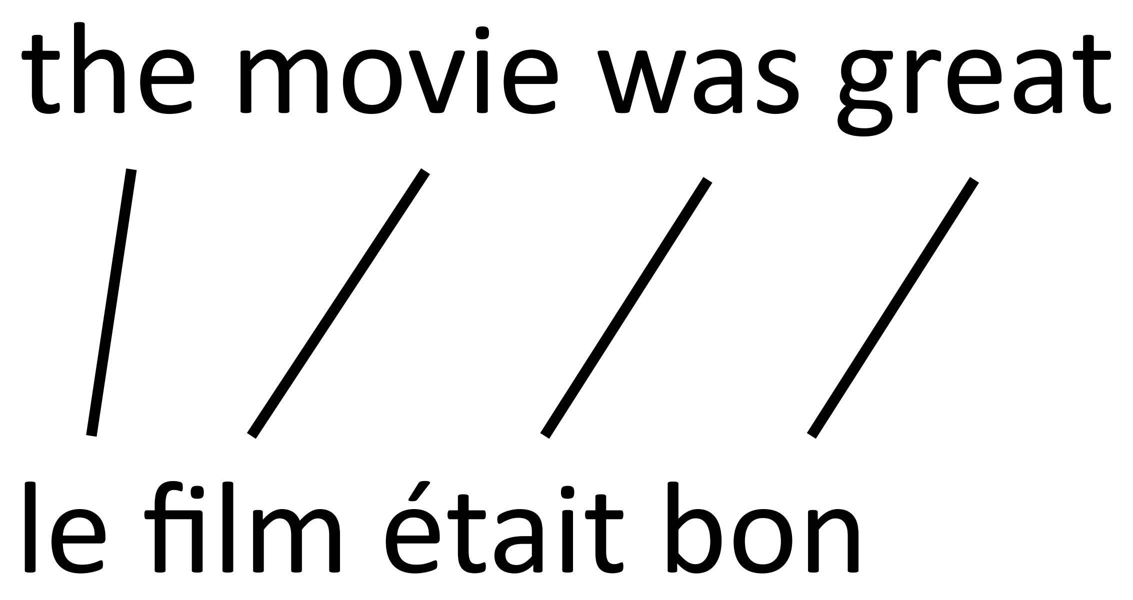
- Suppose we knew the source and target would be word-by-word translated



Aligned Inputs

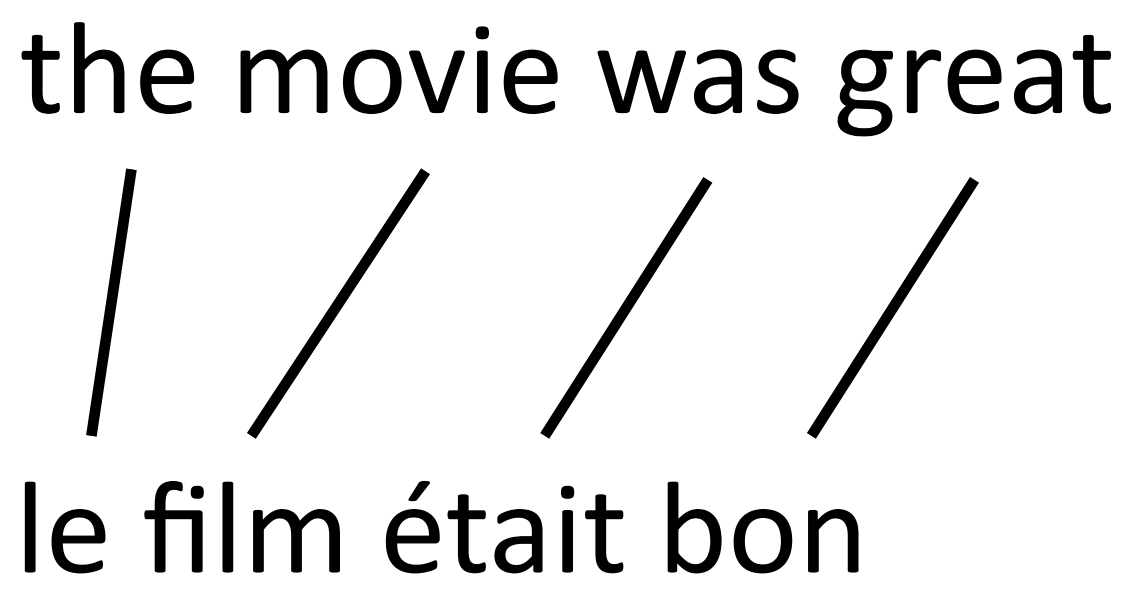
- Suppose we knew the source and target would be word-by-word translated

- Can look at the corresponding input word when translating — this could scale!

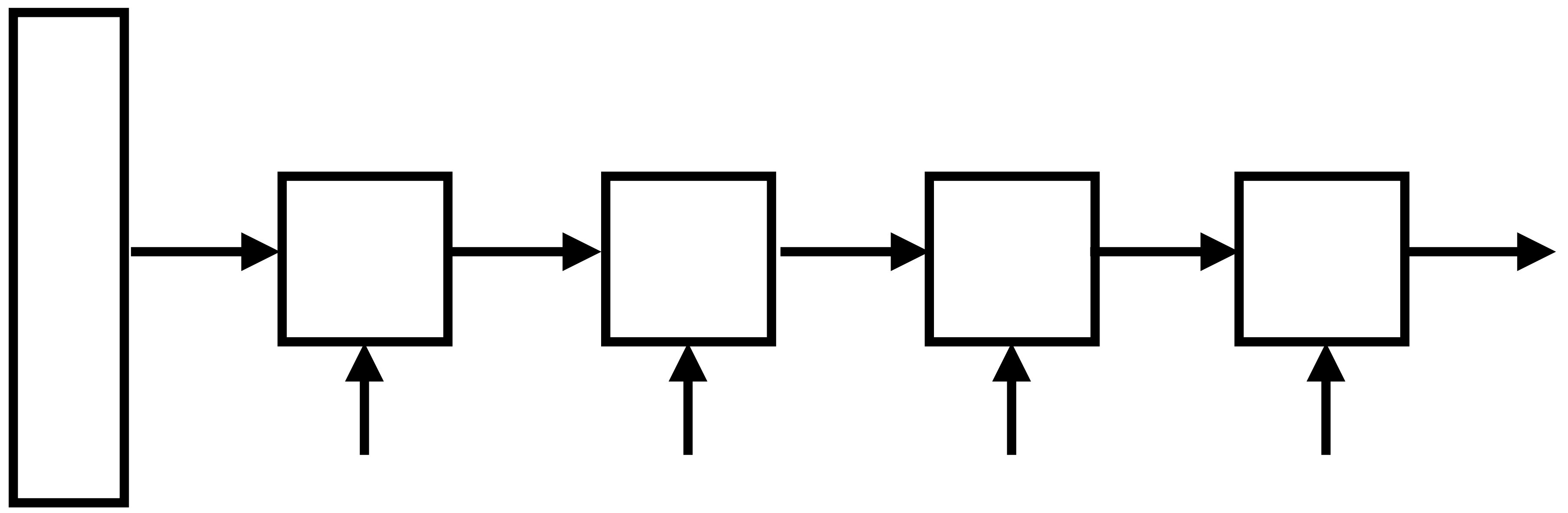


Aligned Inputs

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

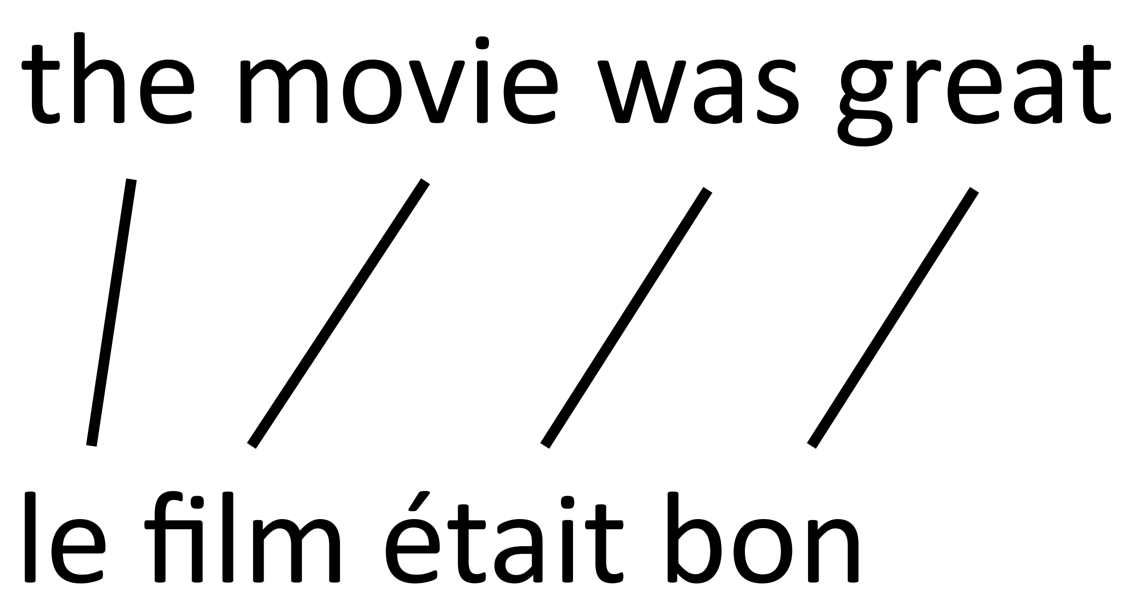


- Can look at the corresponding input word when translating — this could scale!

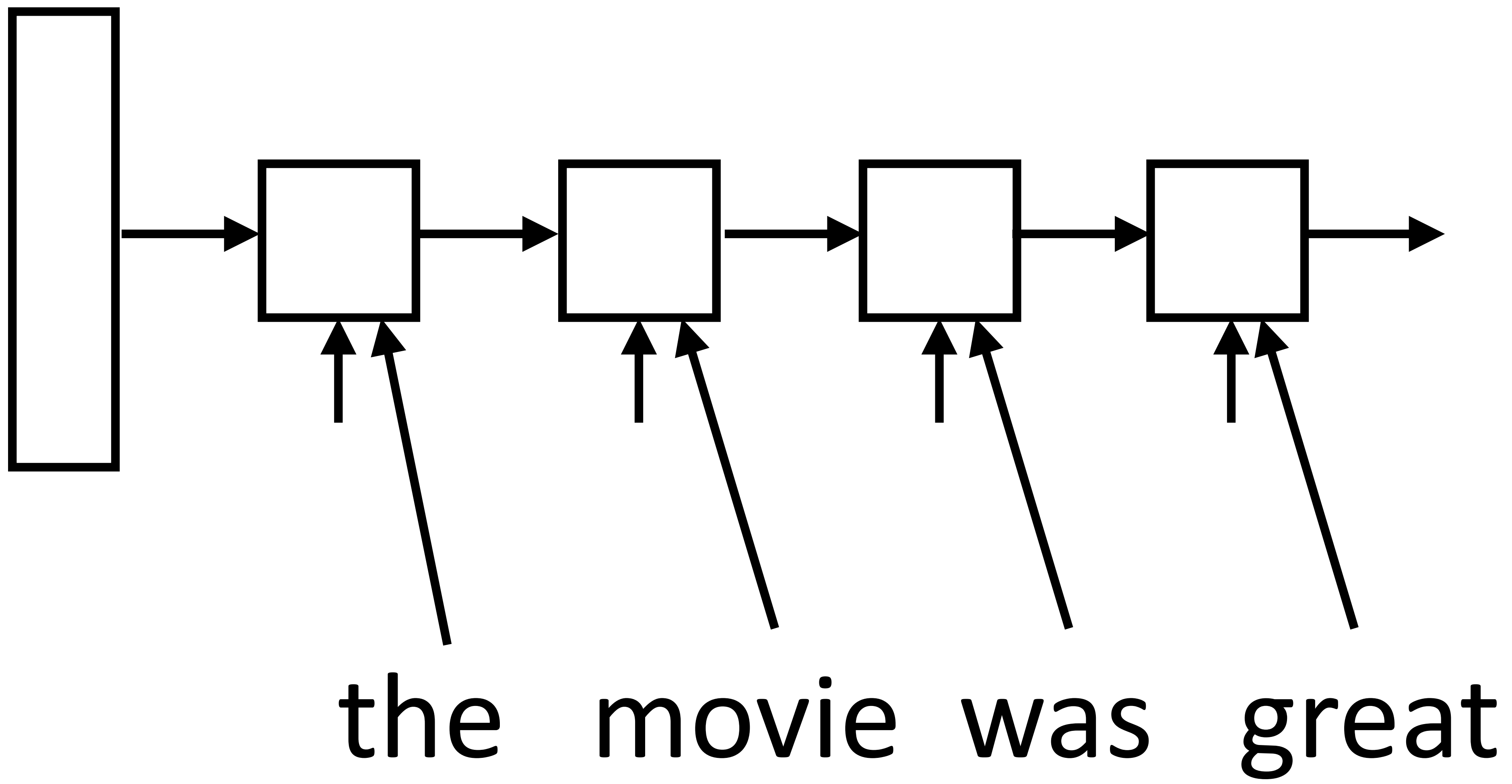


Aligned Inputs

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



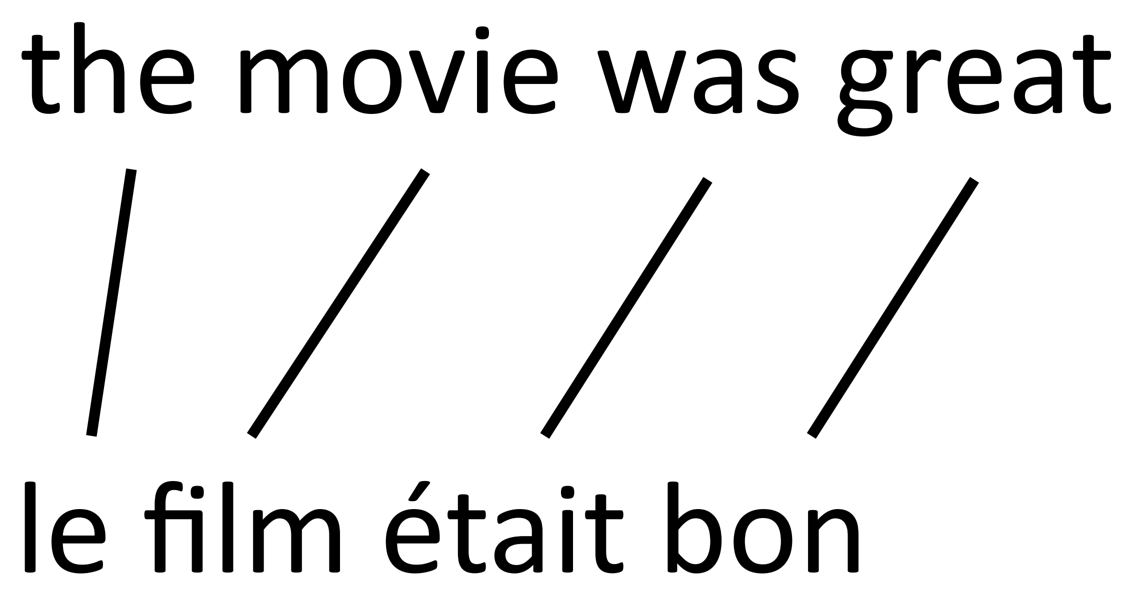
- Can look at the corresponding input word when translating — this could scale!

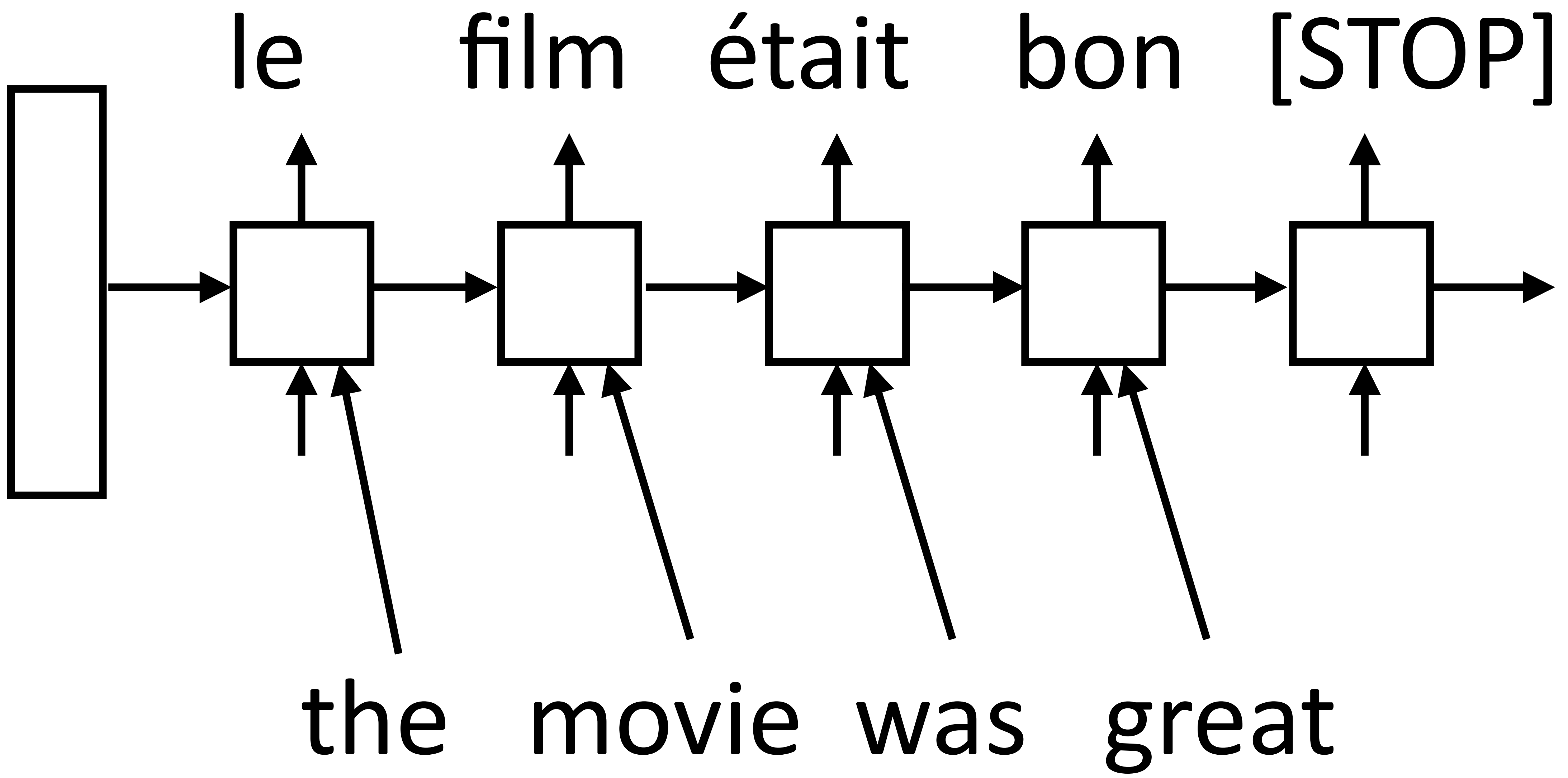


Aligned Inputs

- 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!

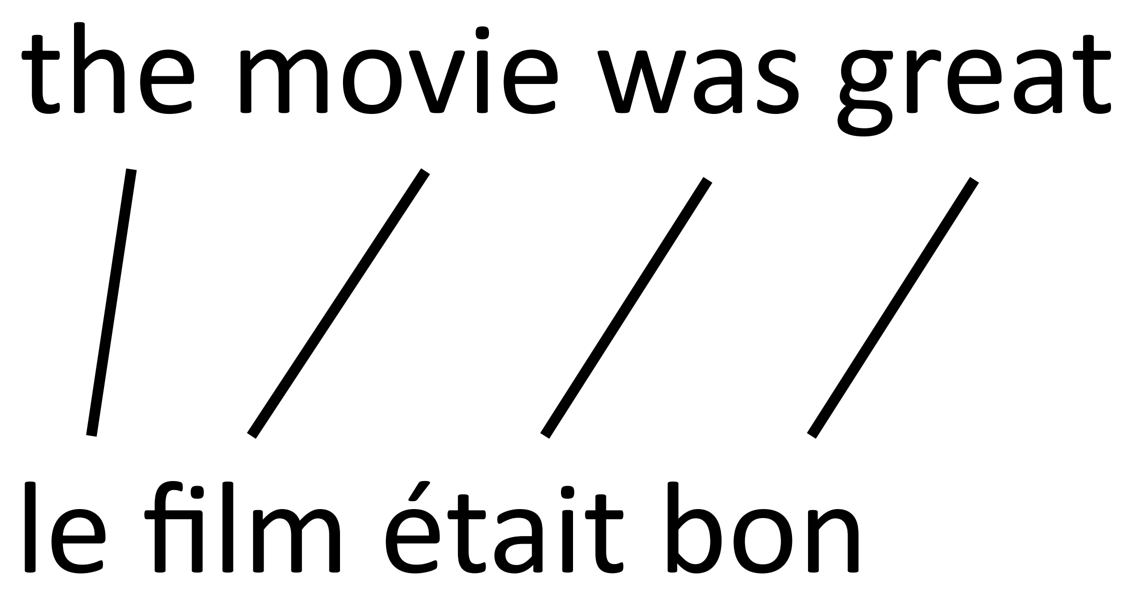


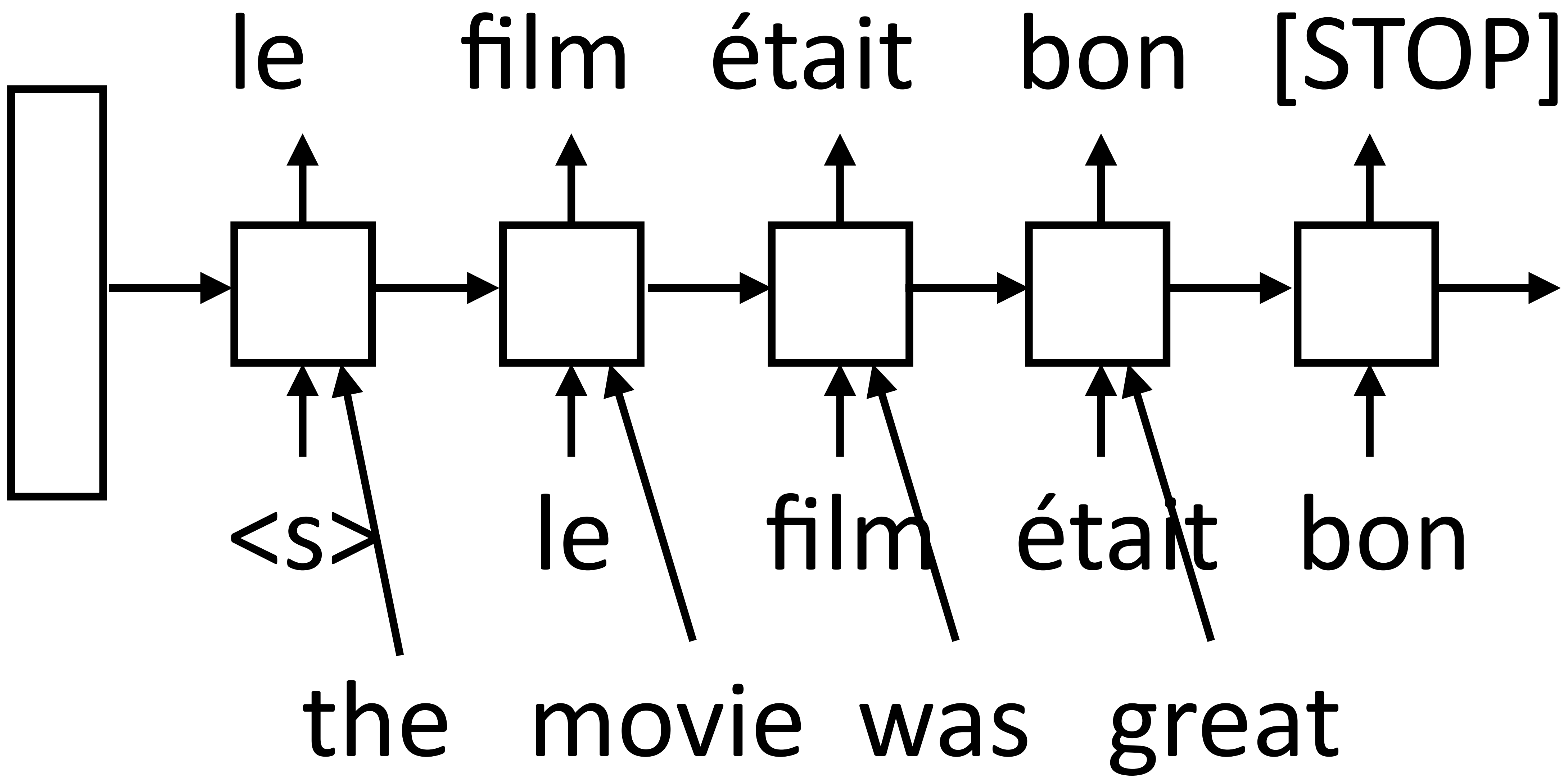


Aligned Inputs

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

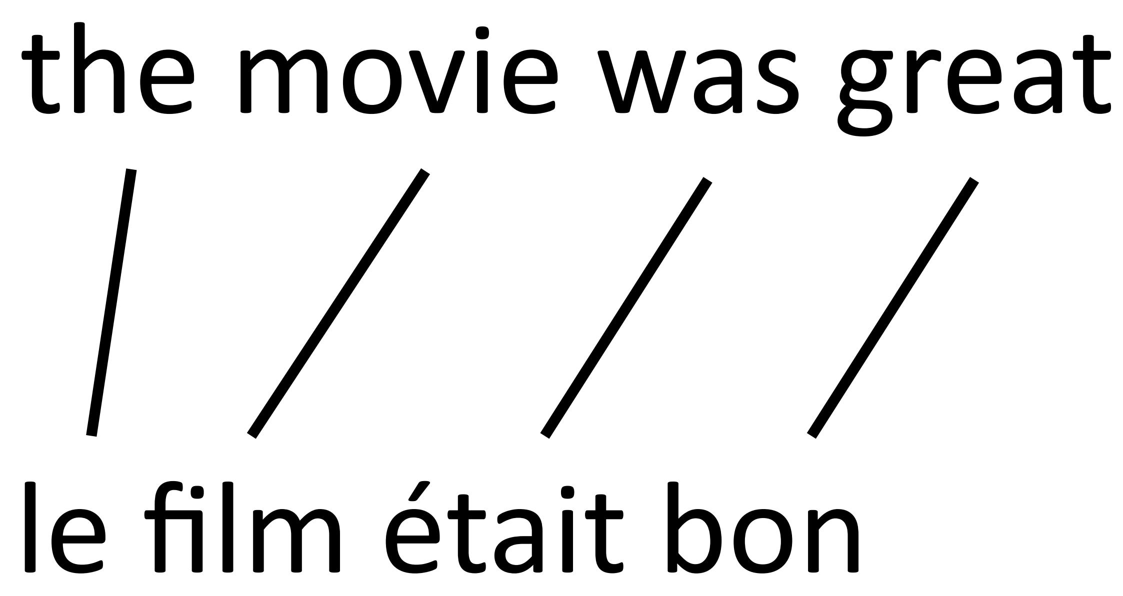
- Can look at the corresponding input word when translating — this could scale!

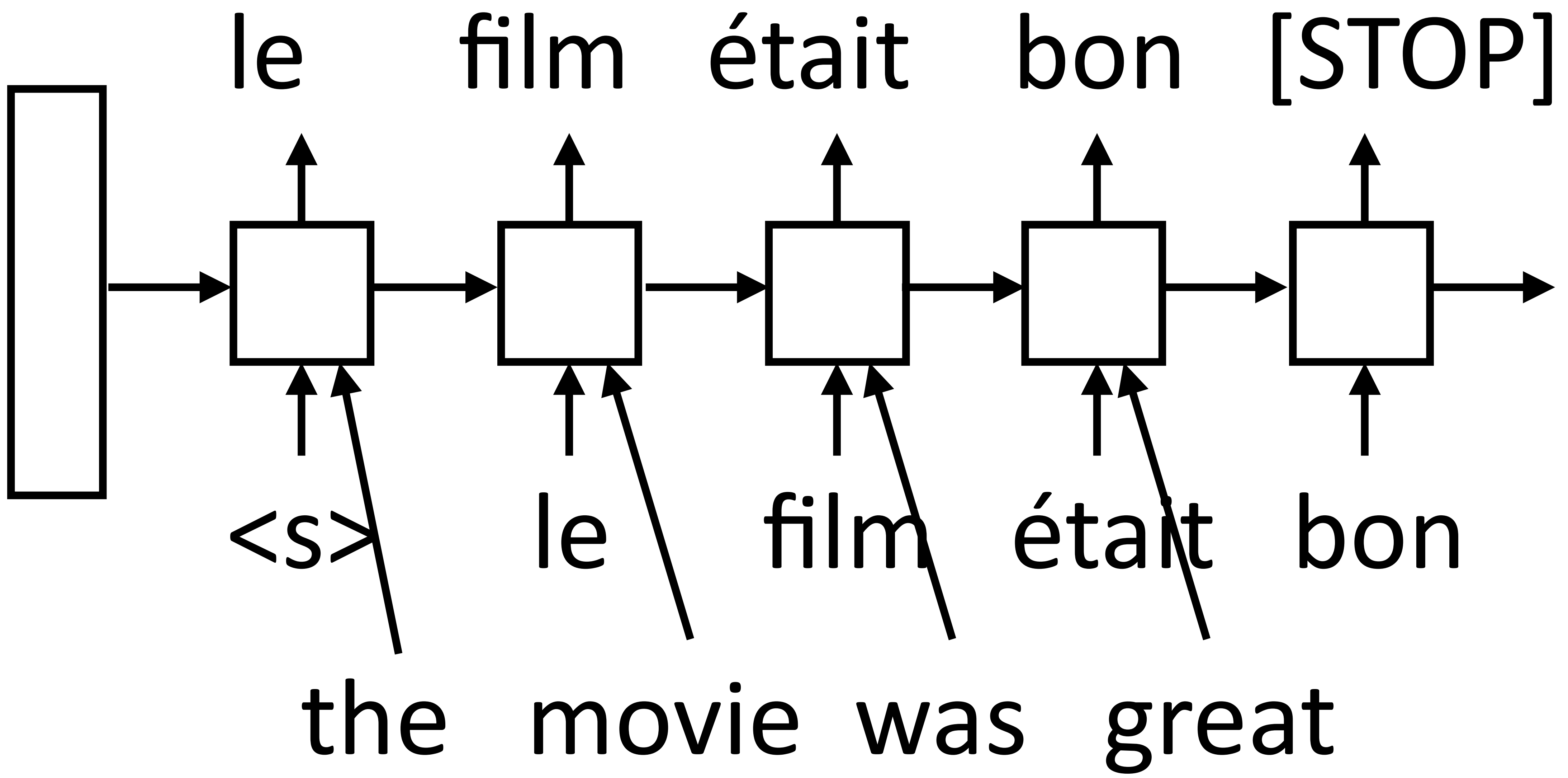




Aligned Inputs

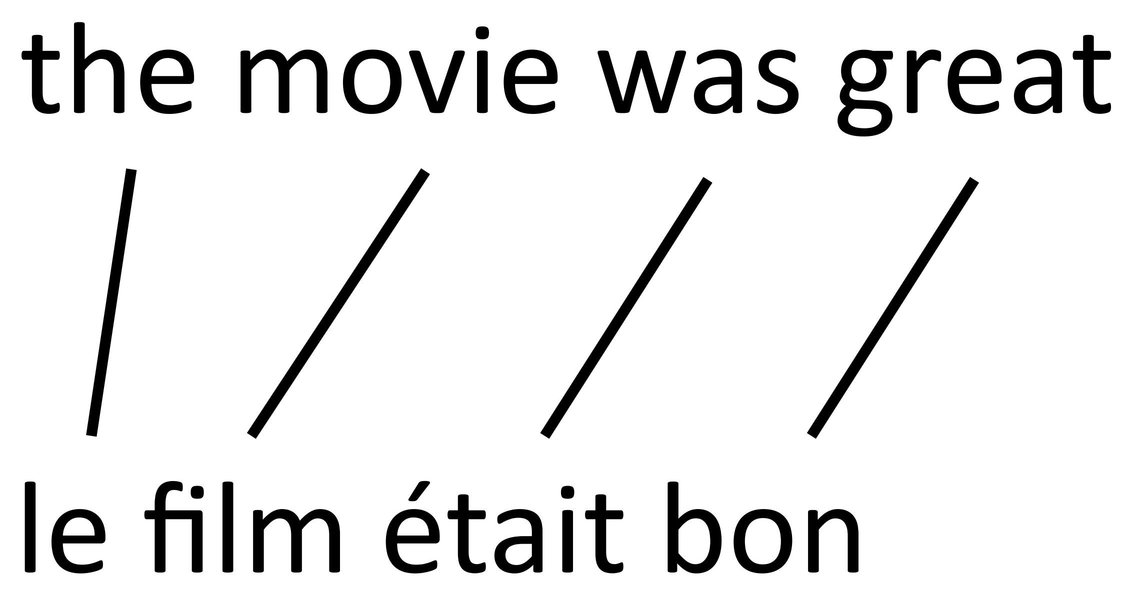
- Suppose we knew the source and target would be word-by-word translated
- Can look at the corresponding input word when translating — this could scale!
- Much less burden on the hidden state



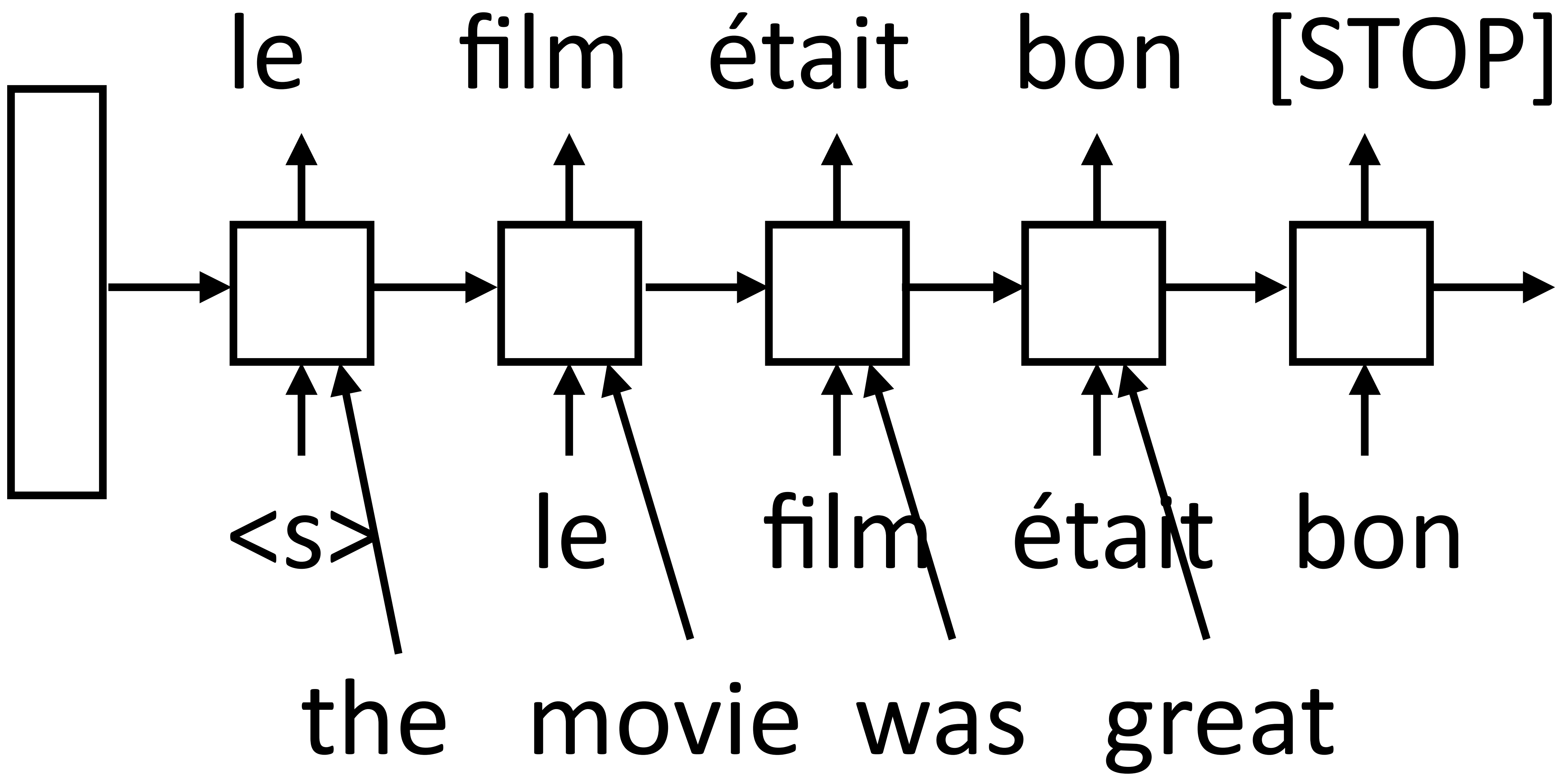


Aligned Inputs

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



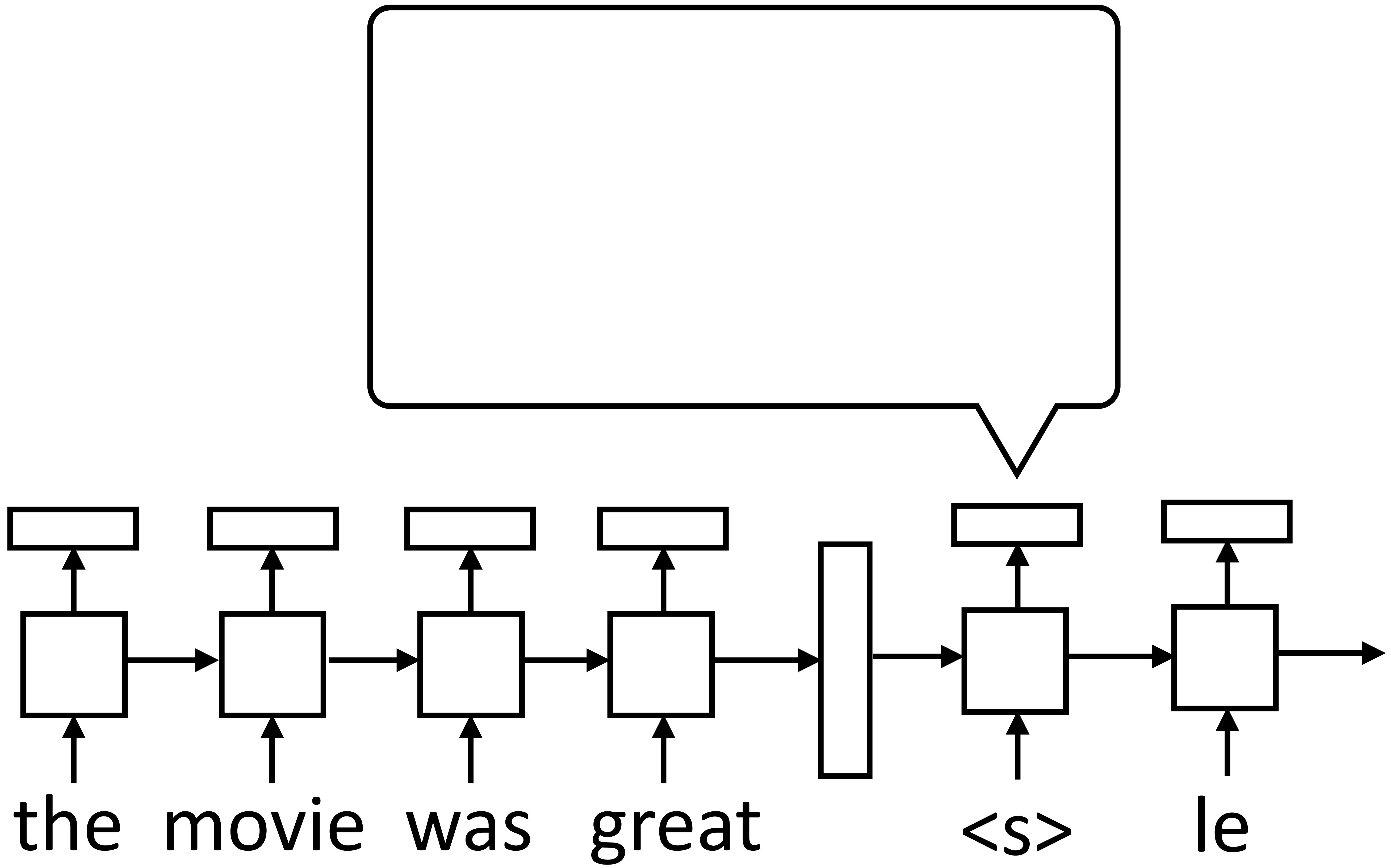
- Can look at the corresponding input word when translating — this could scale!



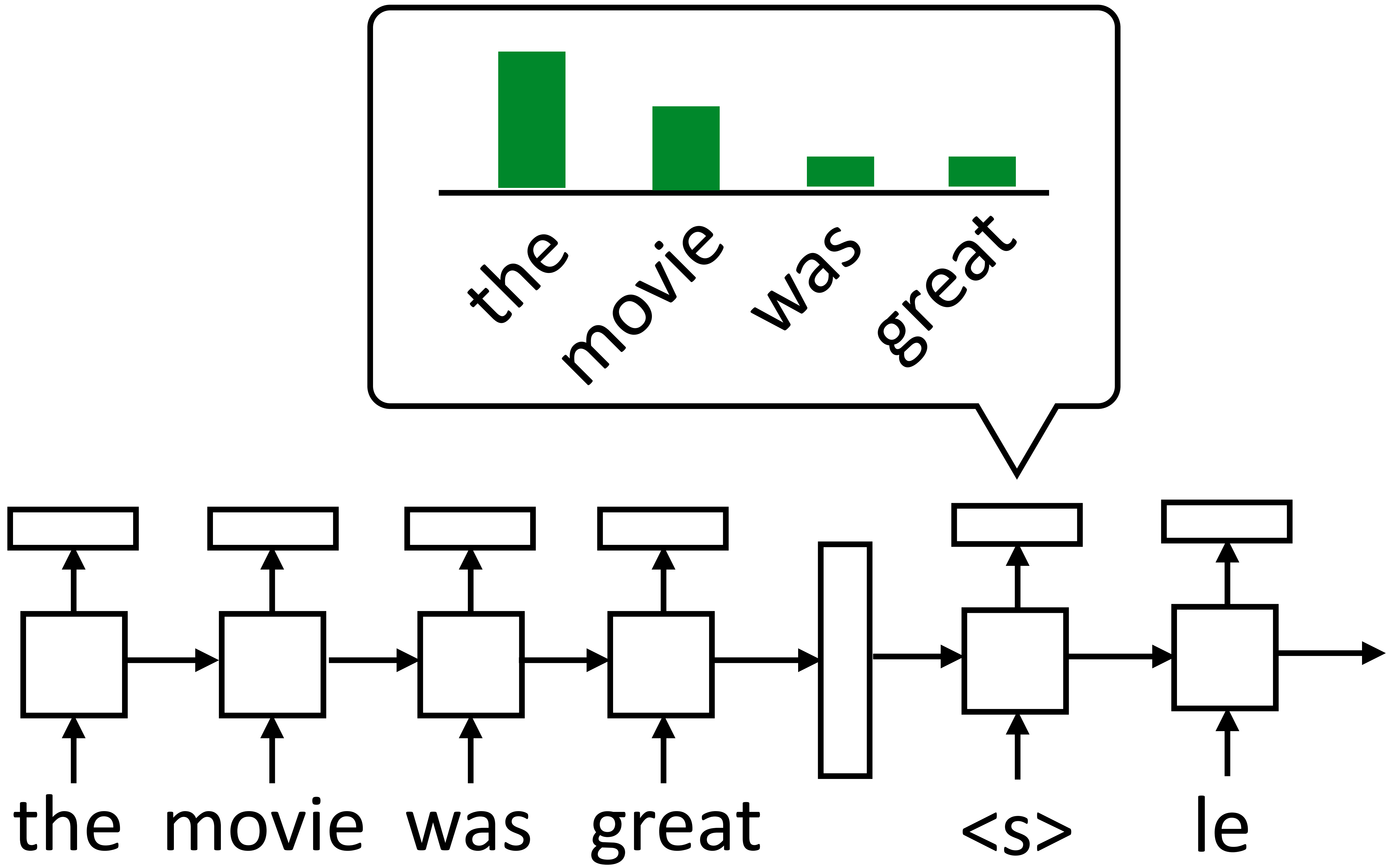
- Much less burden on the hidden state

- How can we achieve this without hardcoding it?

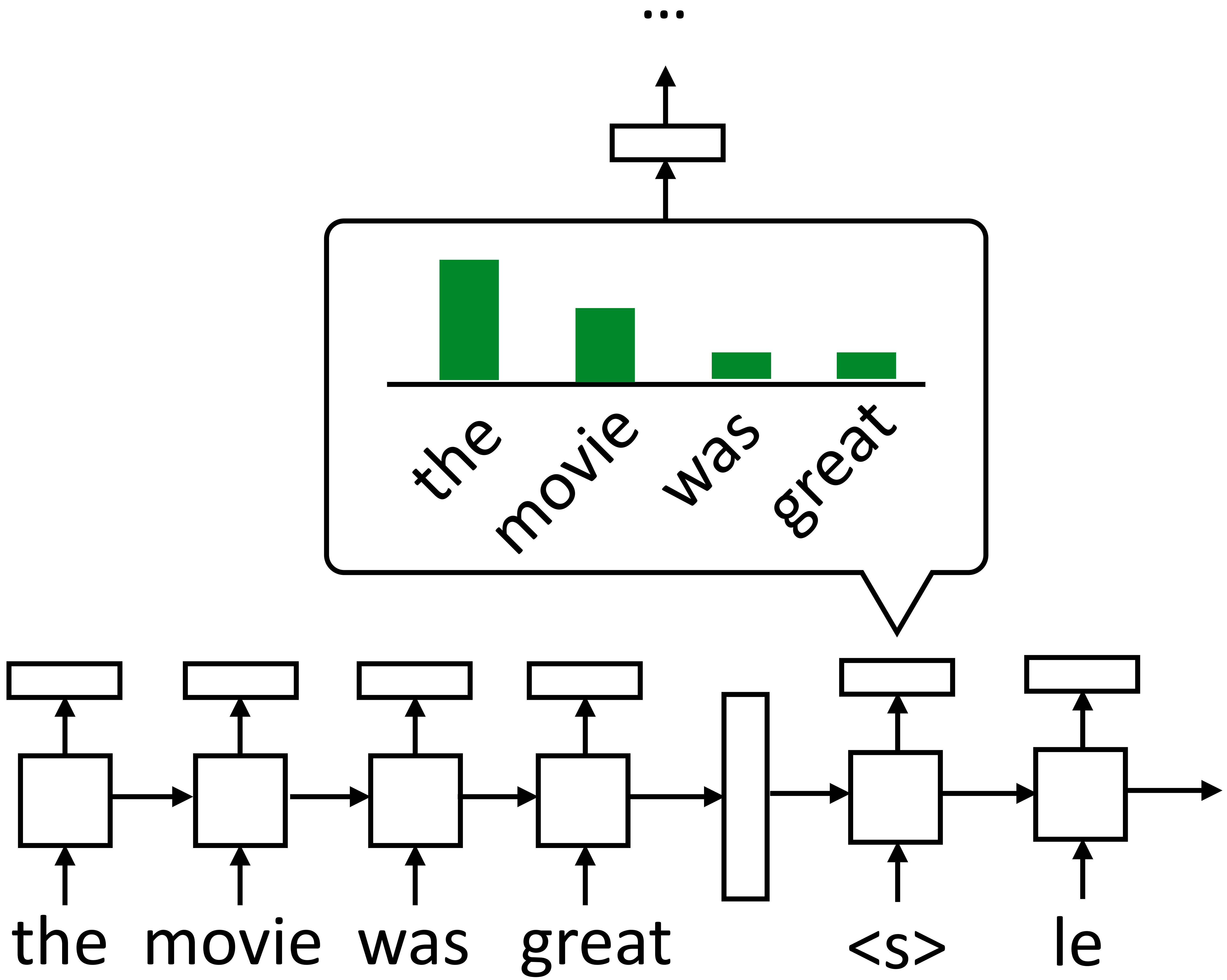
Attention



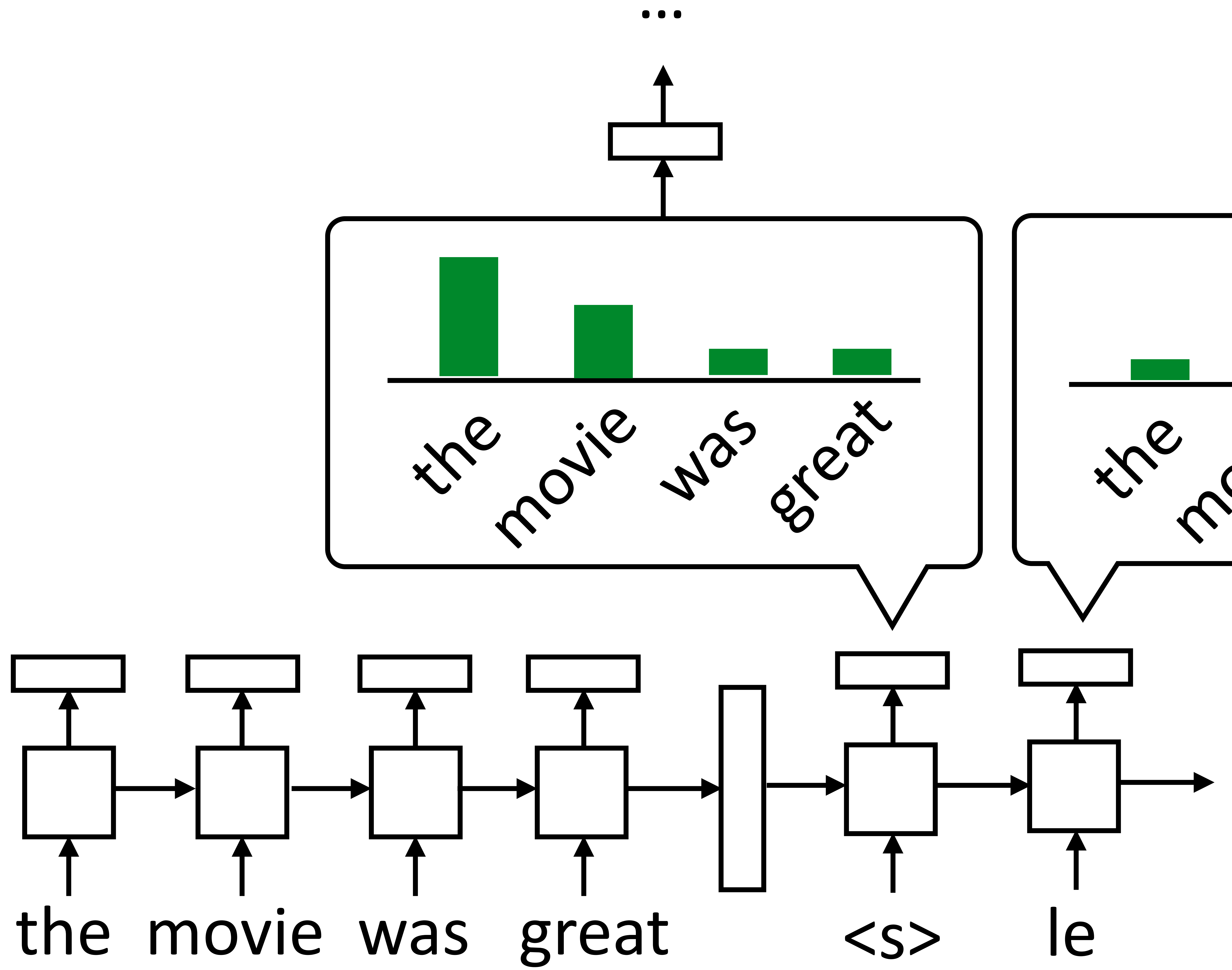
Attention



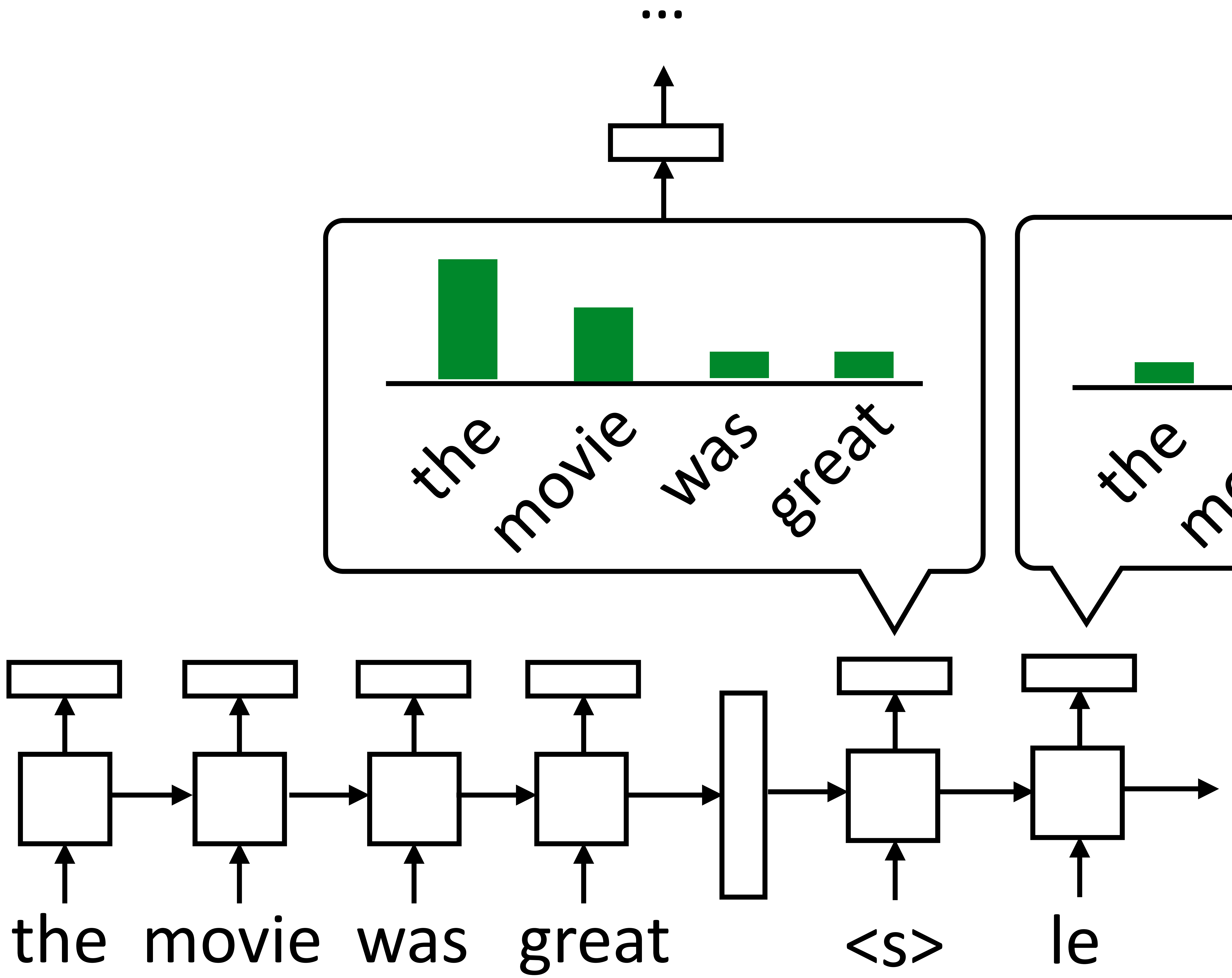
Attention



Attention

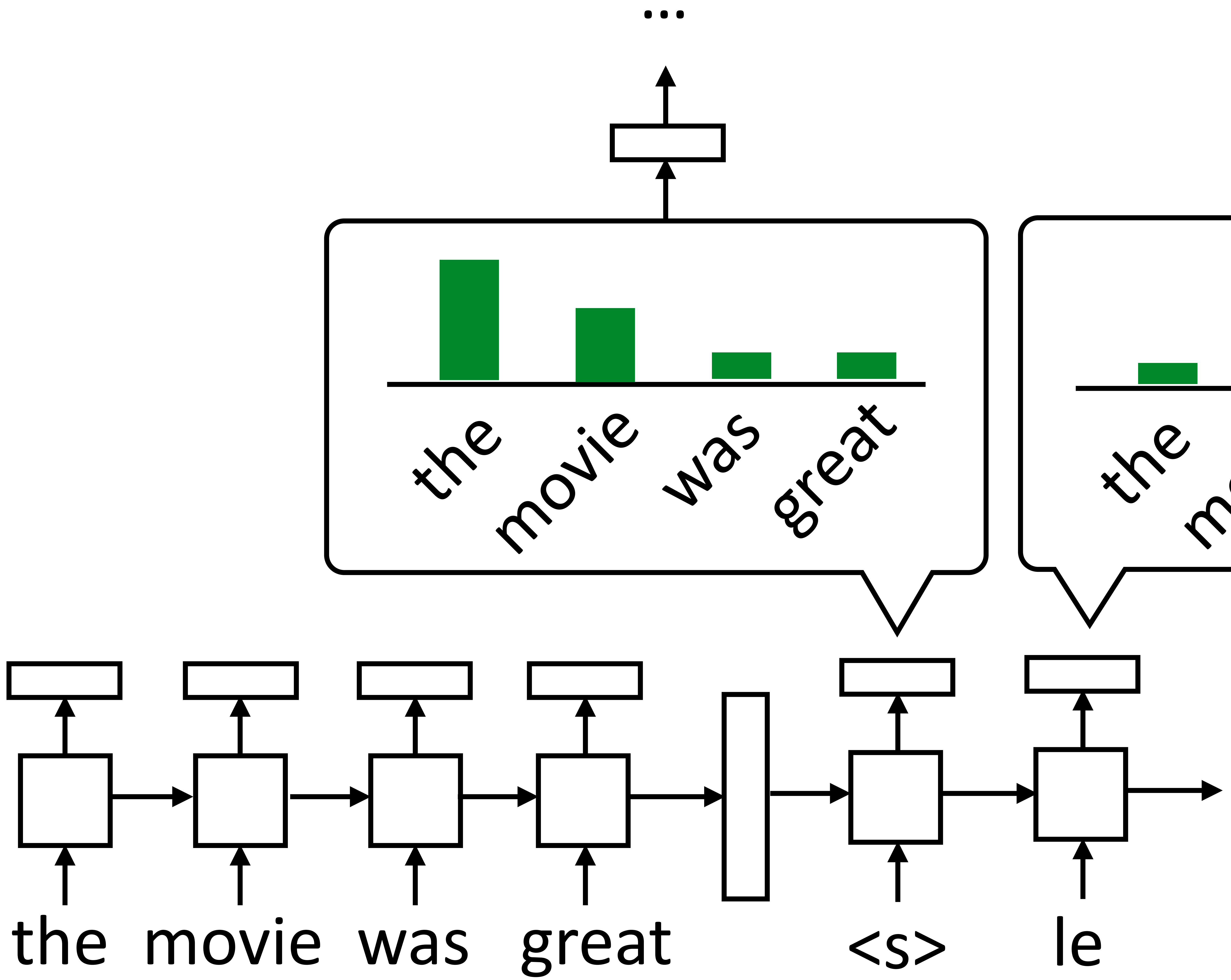

...
the
movie
was
great
the
movie
was
great
the movie was great
<s>
le

Attention



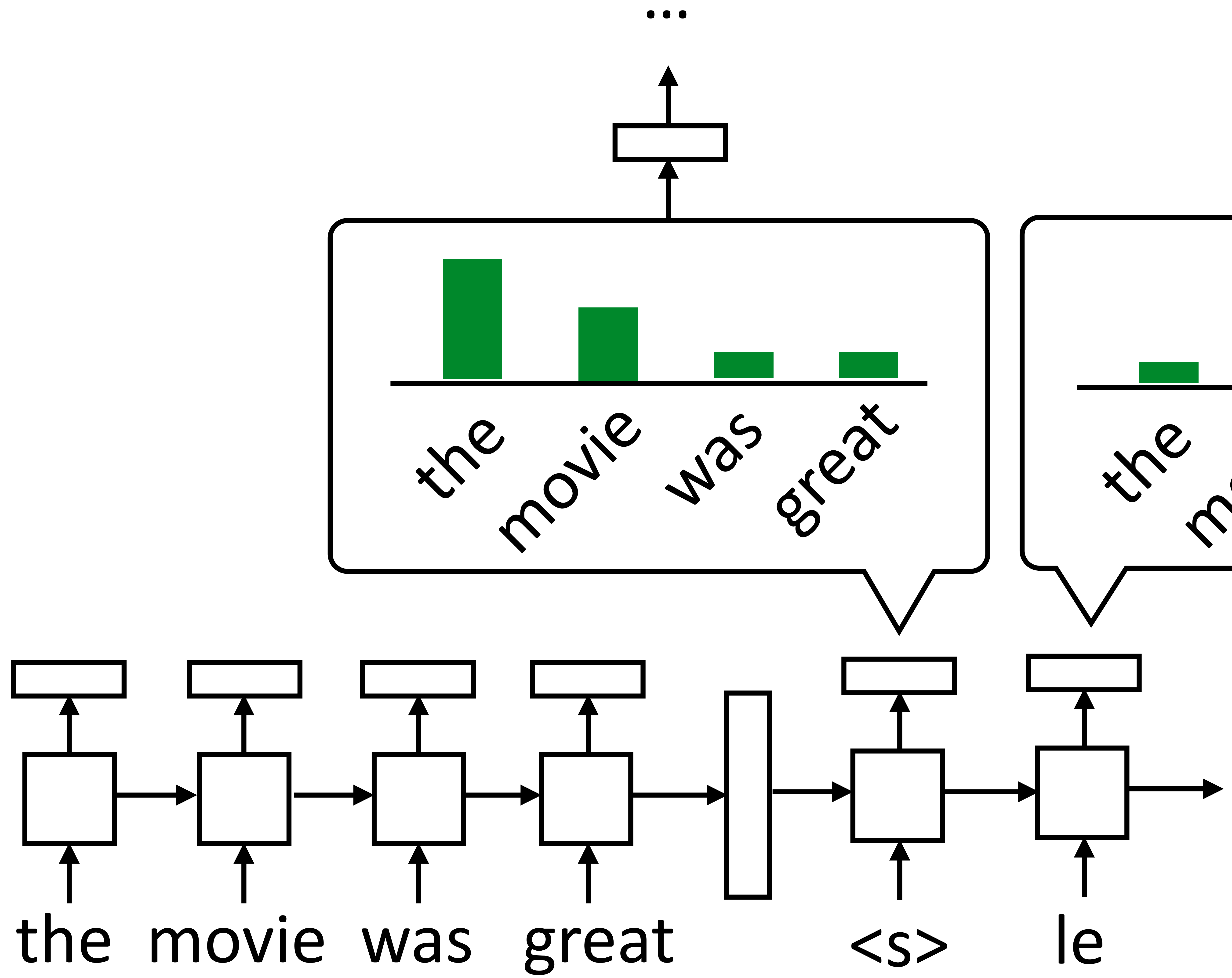
...
...
the
movie
was
great
the
movie
was
great
the
movie
was
great
<s>
le

Attention



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

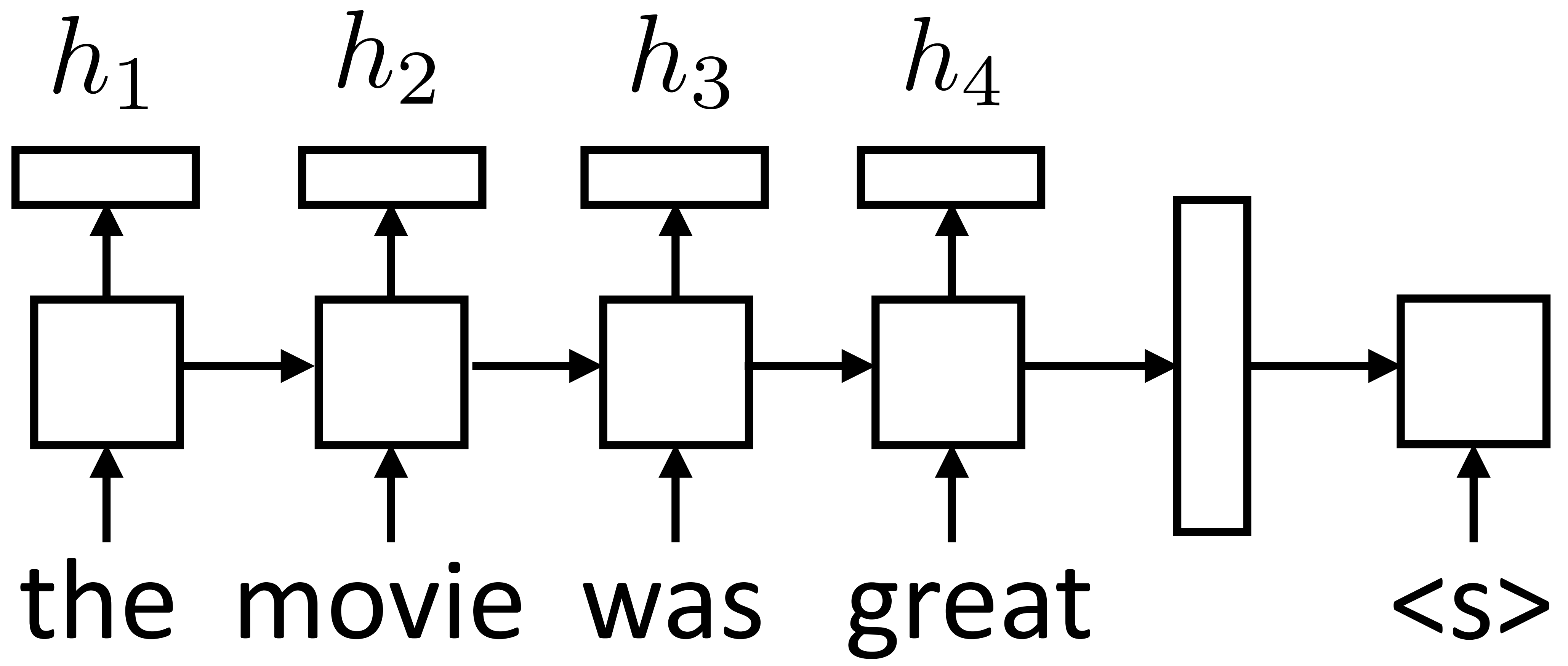
Attention



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

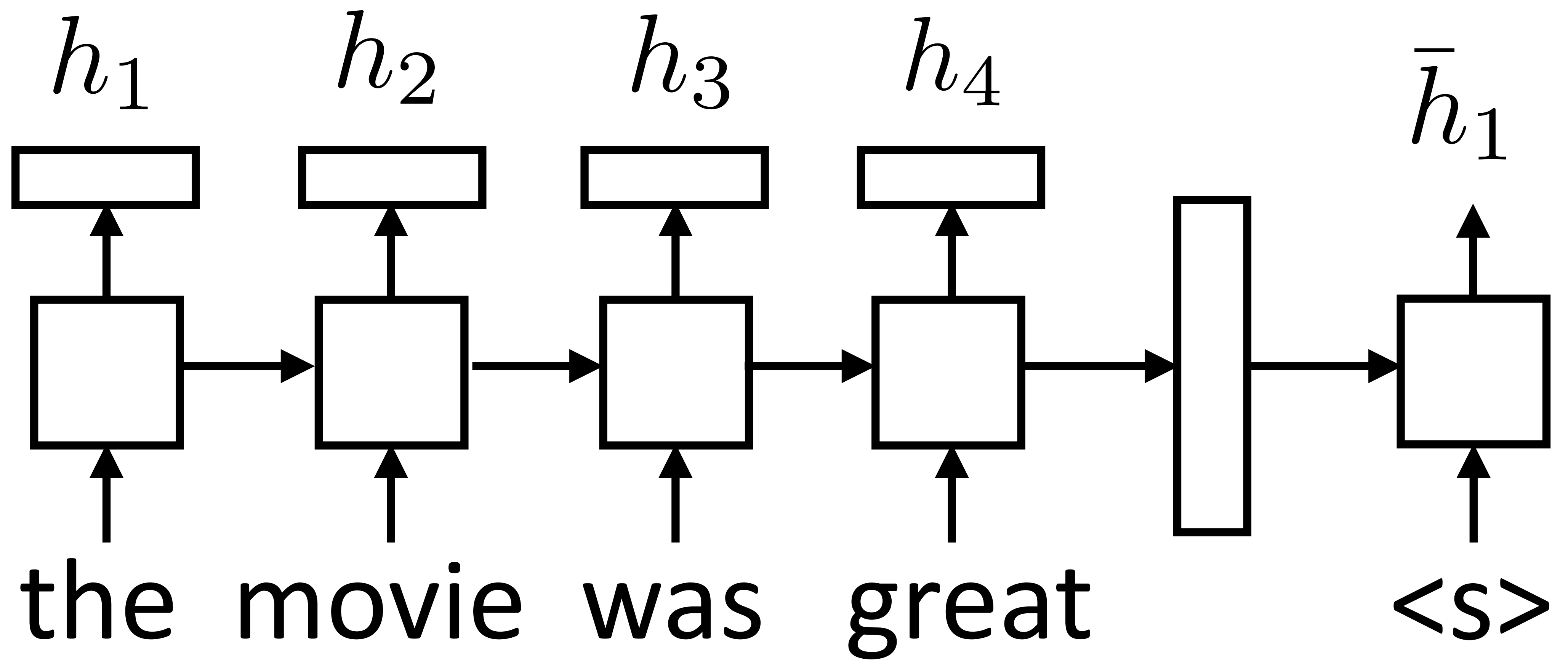
Attention

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



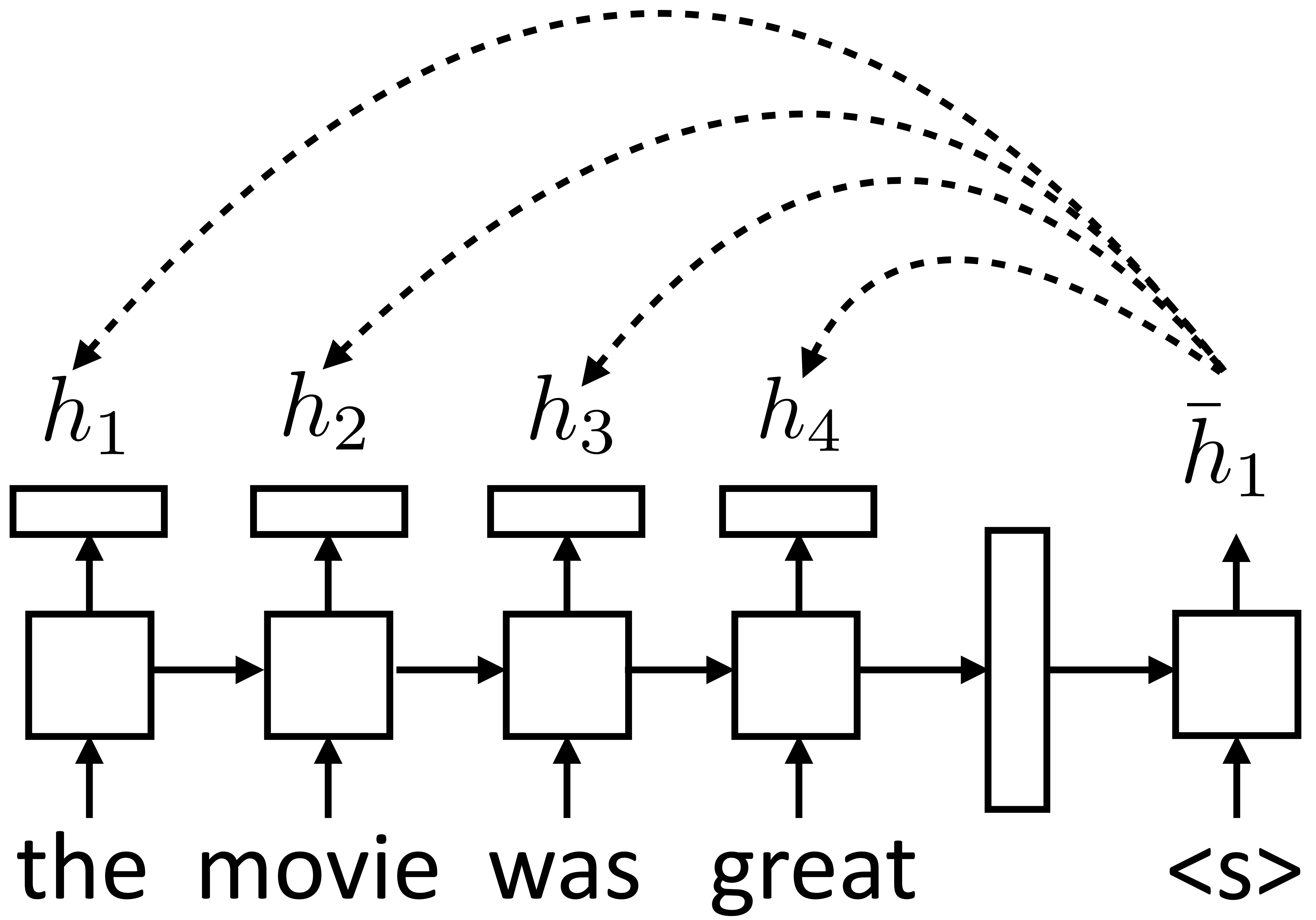
Attention

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



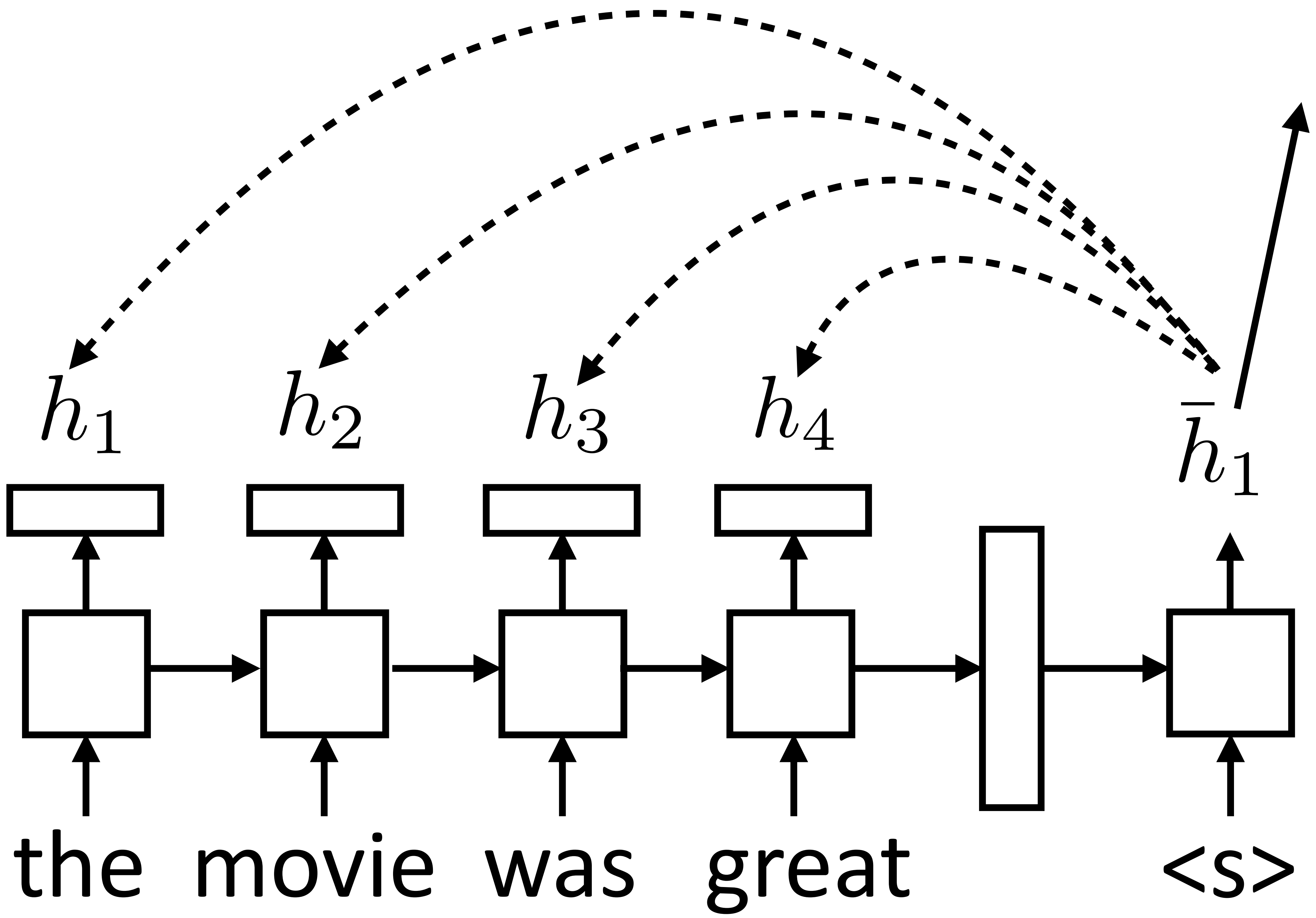
Attention

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



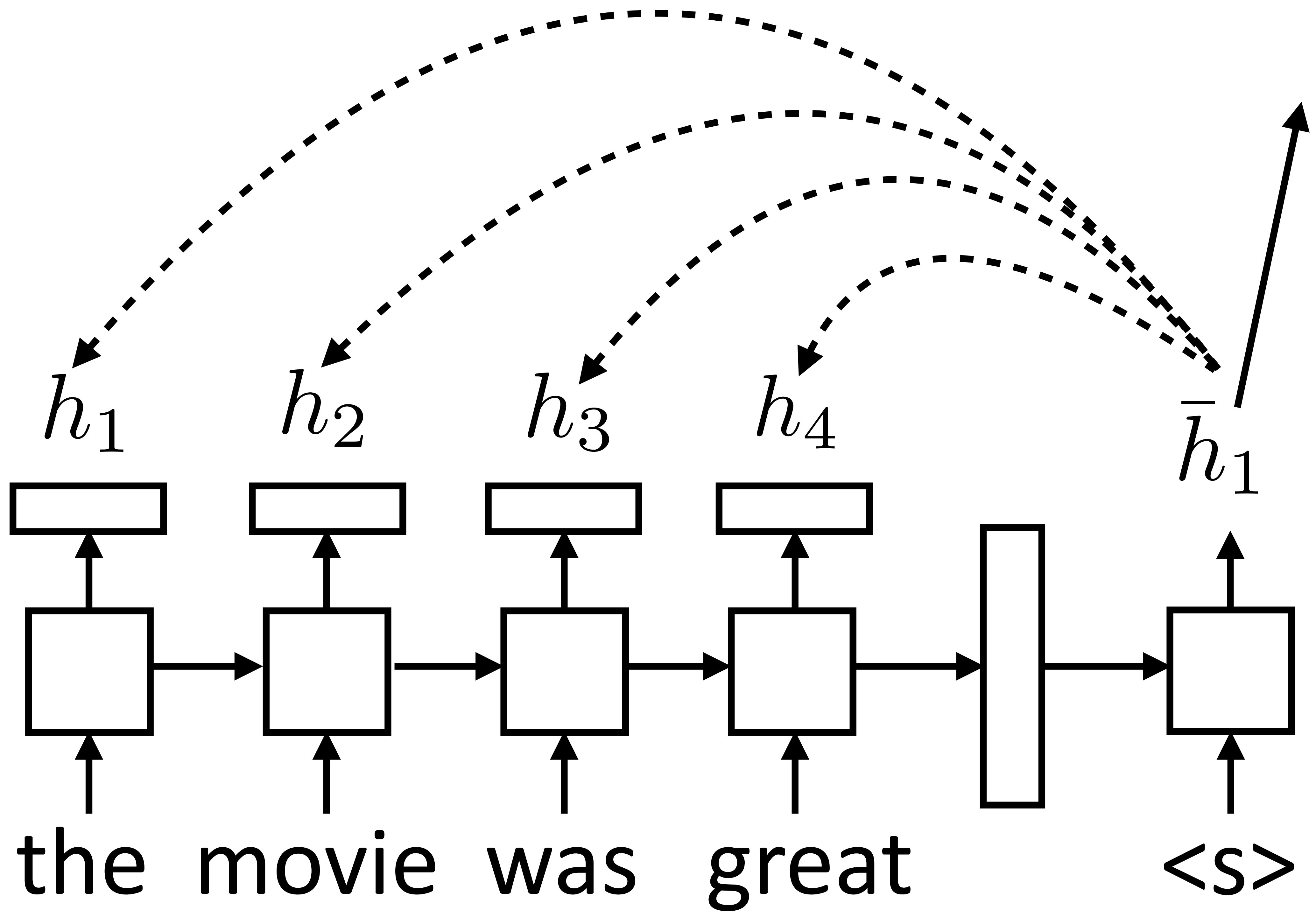
Attention

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



Attention

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

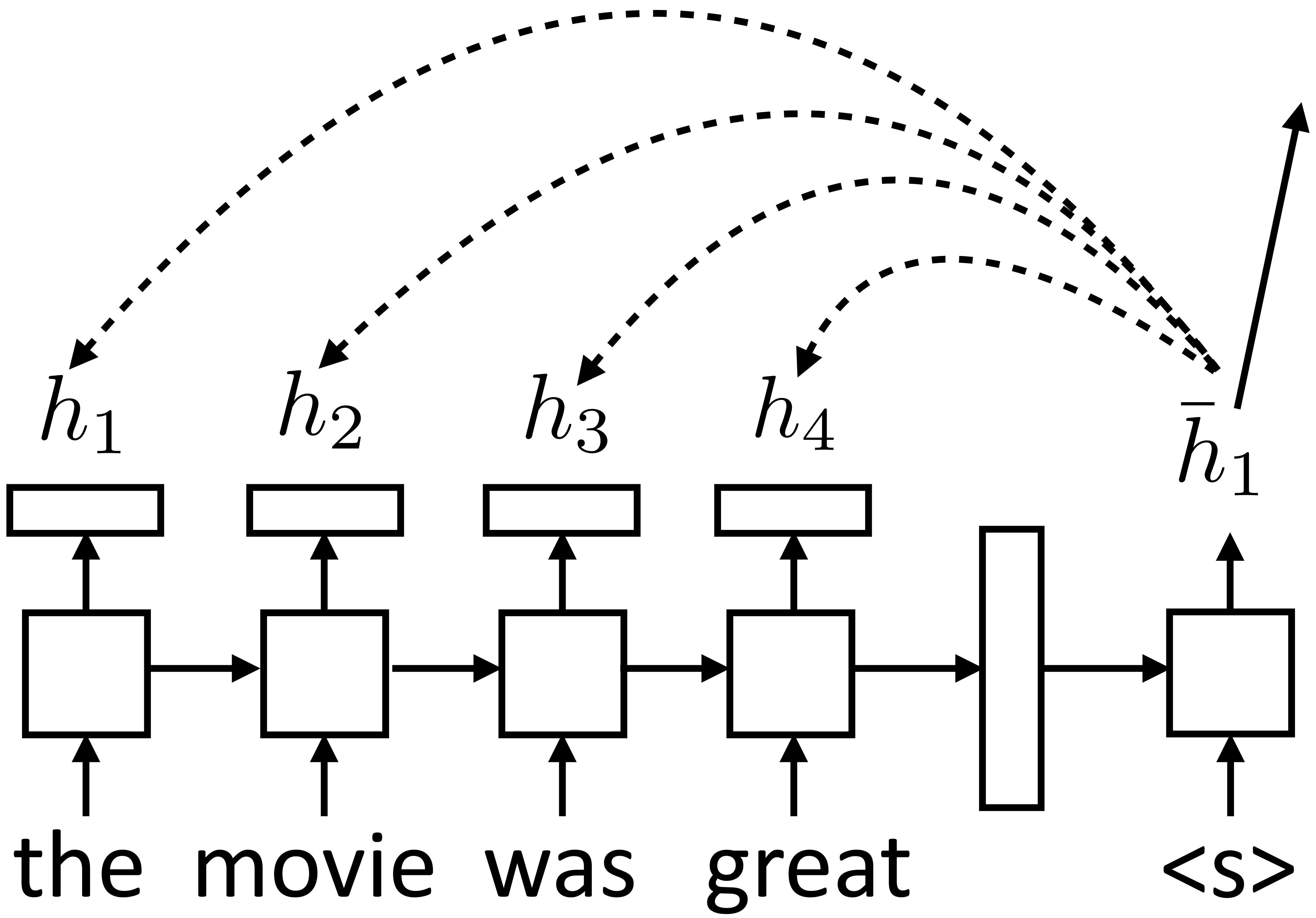


$$e_{ij} = f(\bar{h}_i, h_j)$$

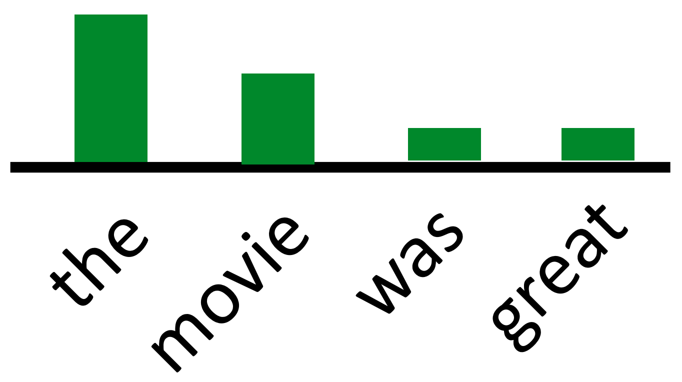
- Unnormalized scalar weight

Attention

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



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

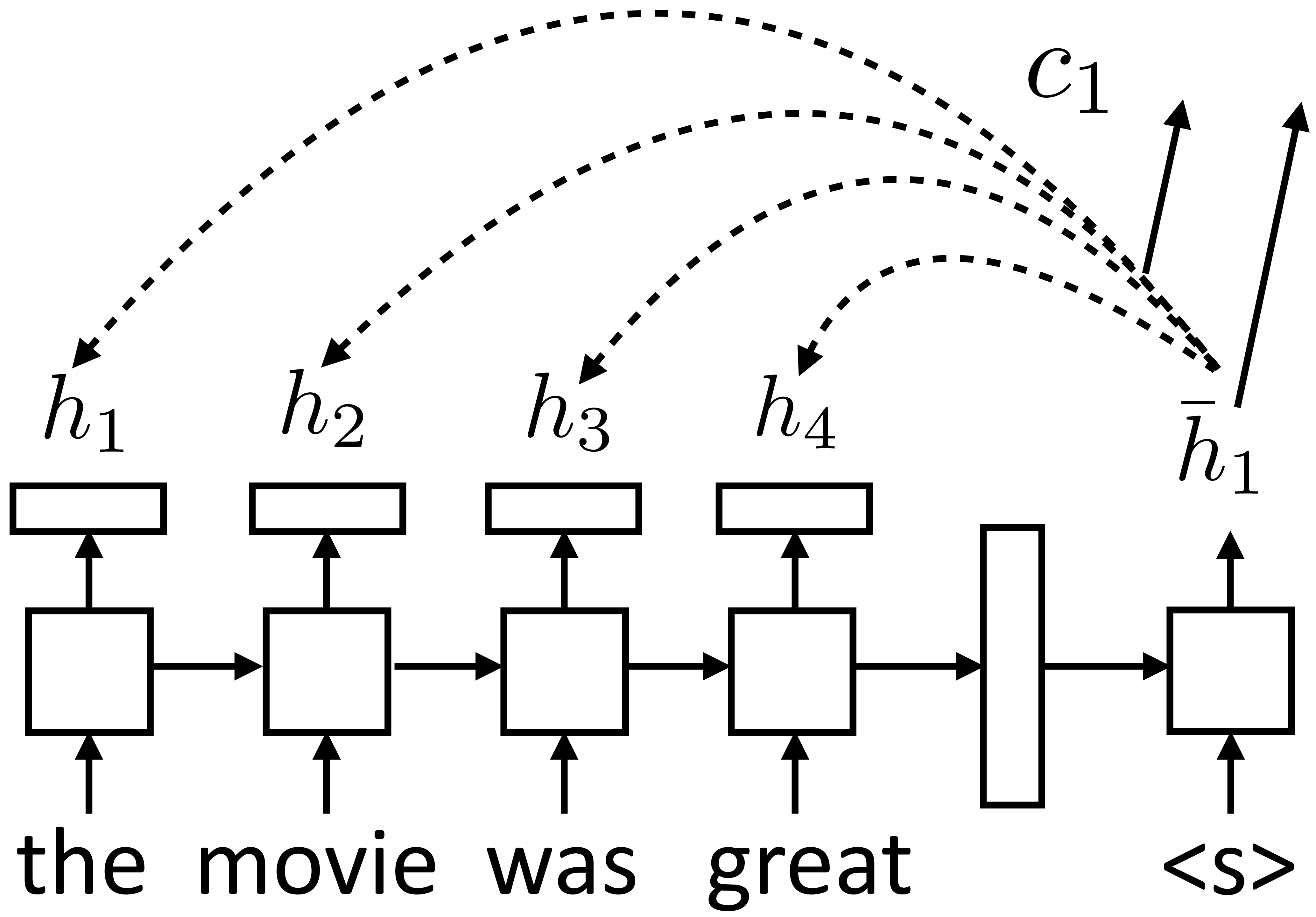


$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

Attention

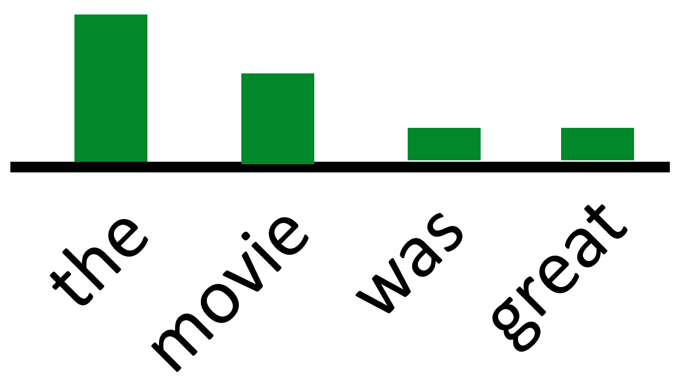
- For each decoder state, compute weighted sum of input states



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

- Weighted sum of input hidden states (vector)

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

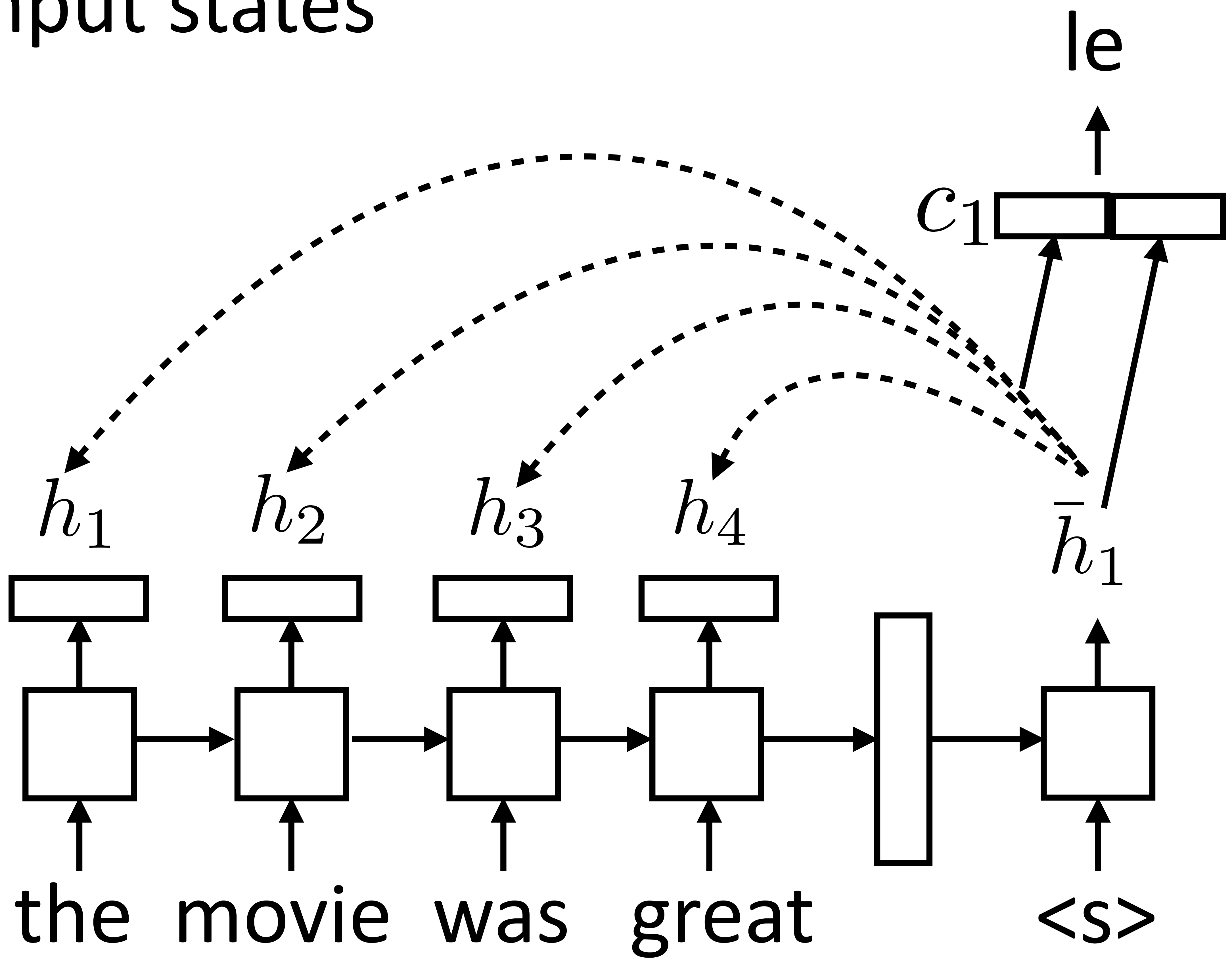


$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

Attention

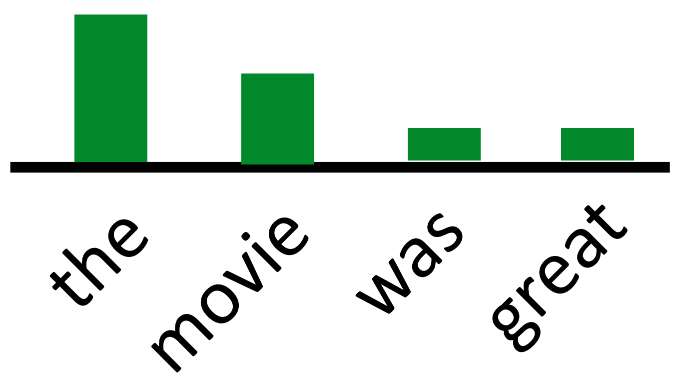
- For each decoder state, compute weighted sum of input states



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

- Weighted sum of input hidden states (vector)

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

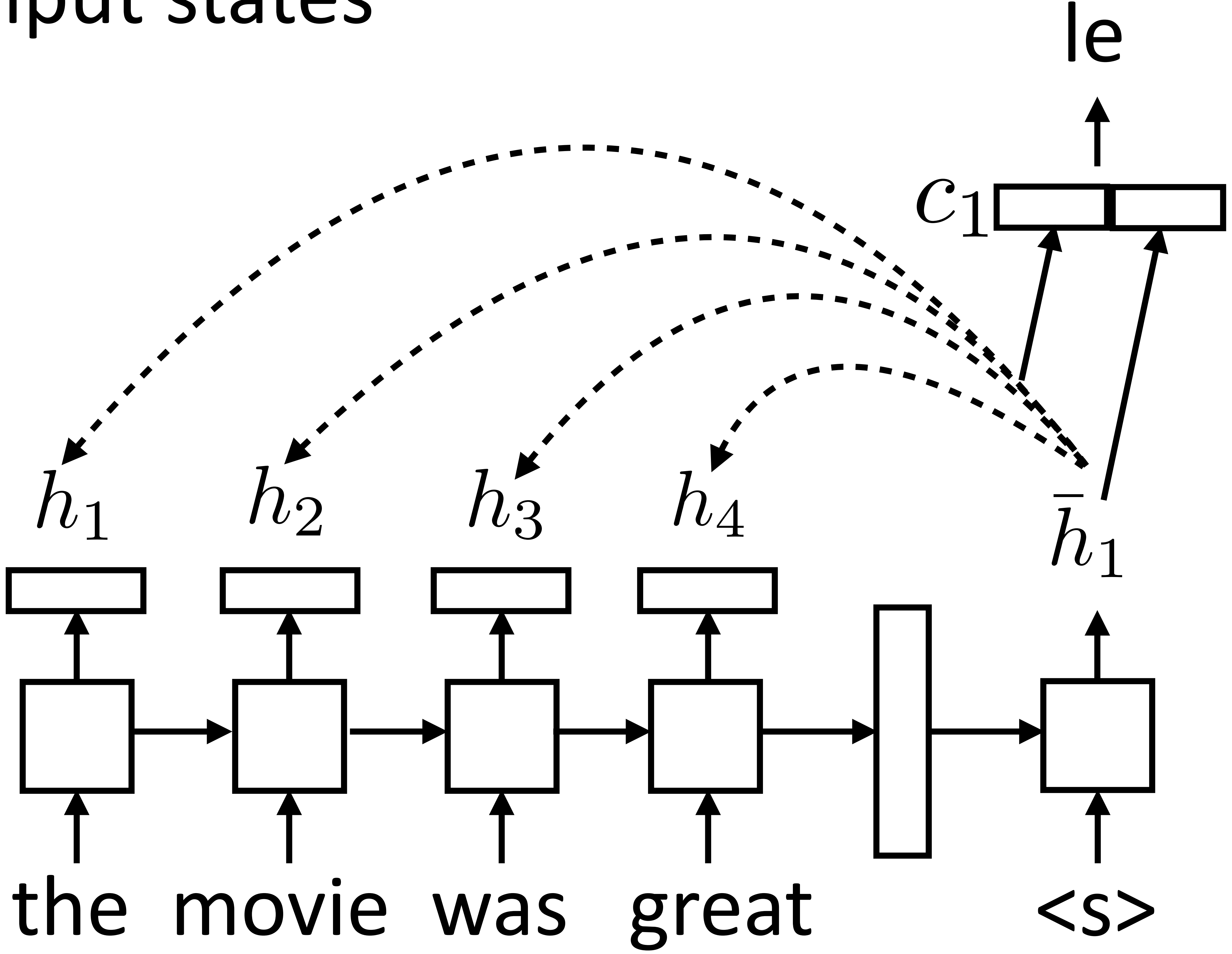


$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

Attention

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

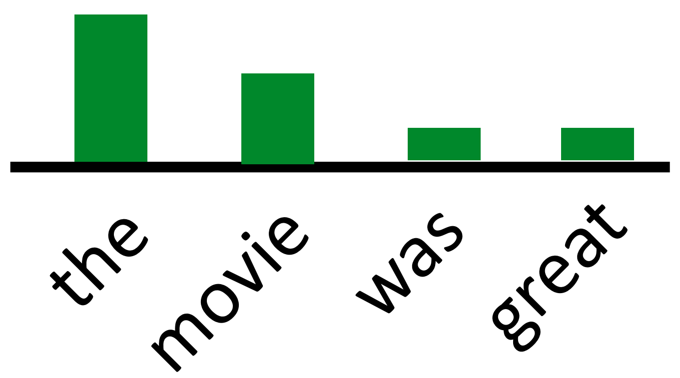


$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W[c_i; \bar{h}_i])$$

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

- Weighted sum of input hidden states (vector)

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

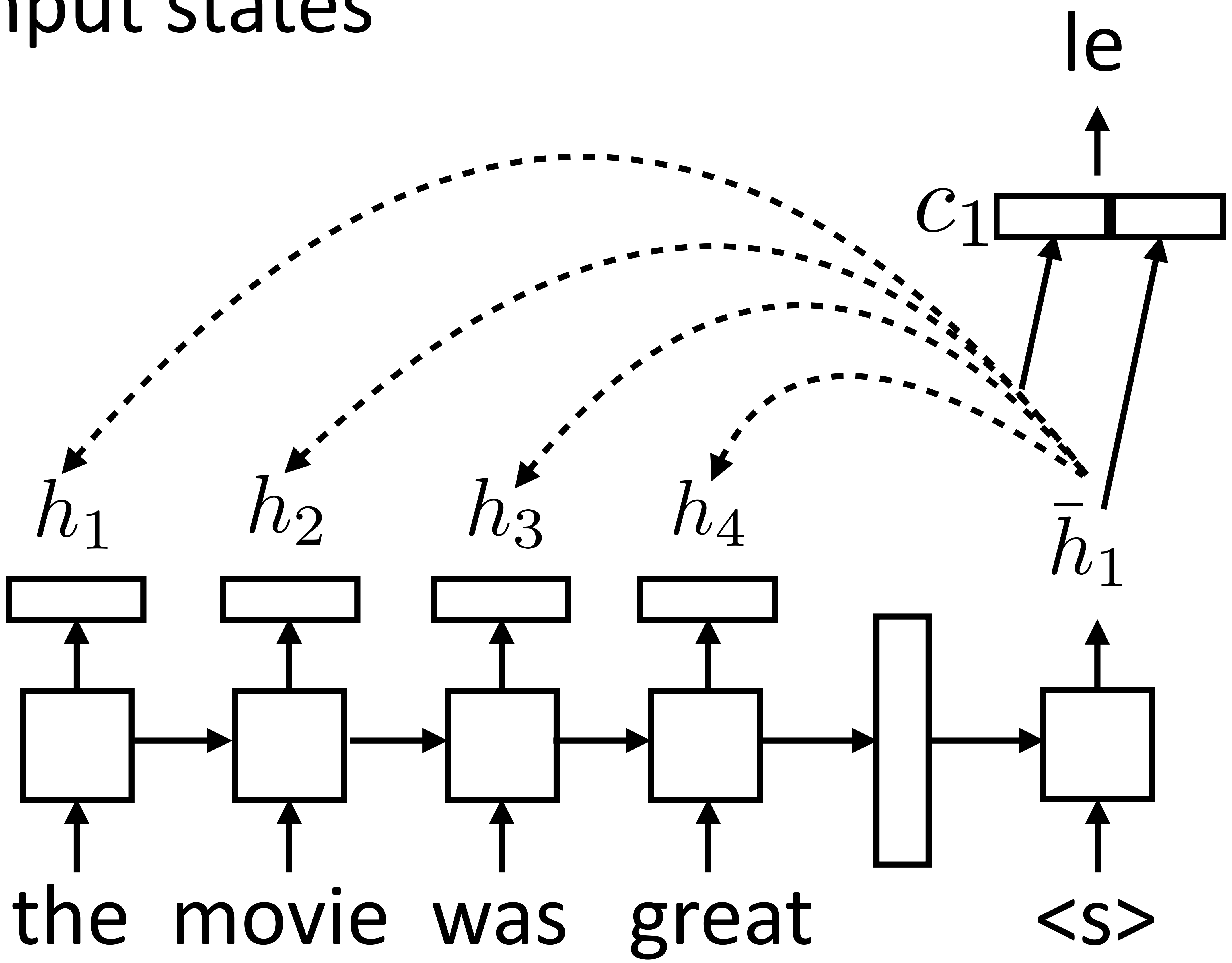


$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

Attention

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



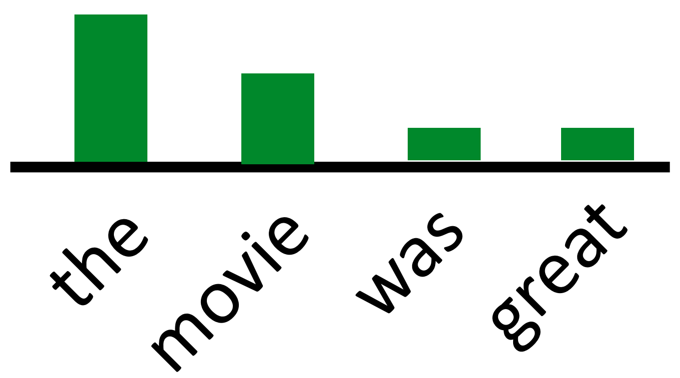
- No attn: $P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W\bar{h}_i)$

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

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

- Weighted sum of input hidden states (vector)

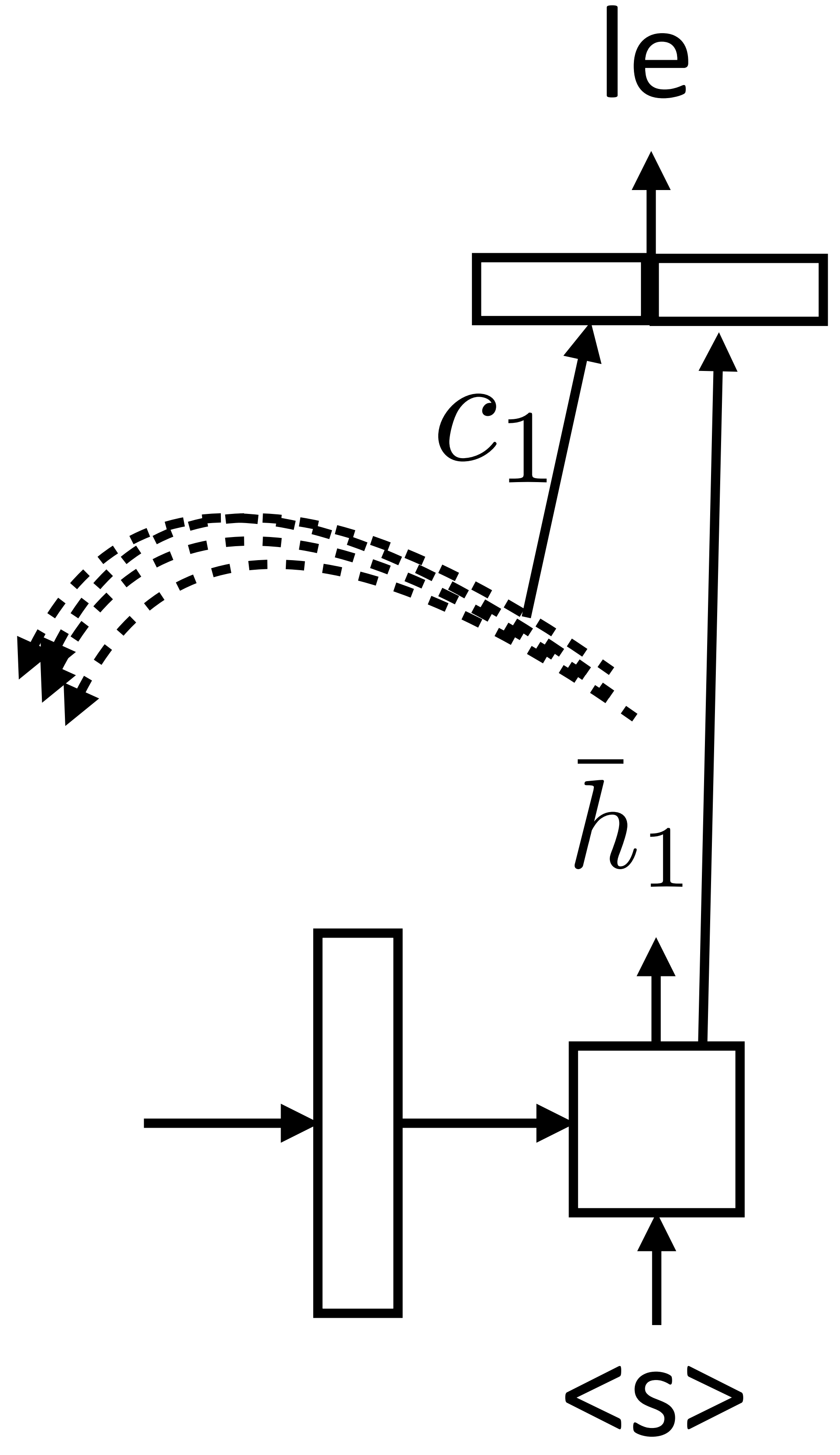
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$



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

- Unnormalized scalar weight

Attention



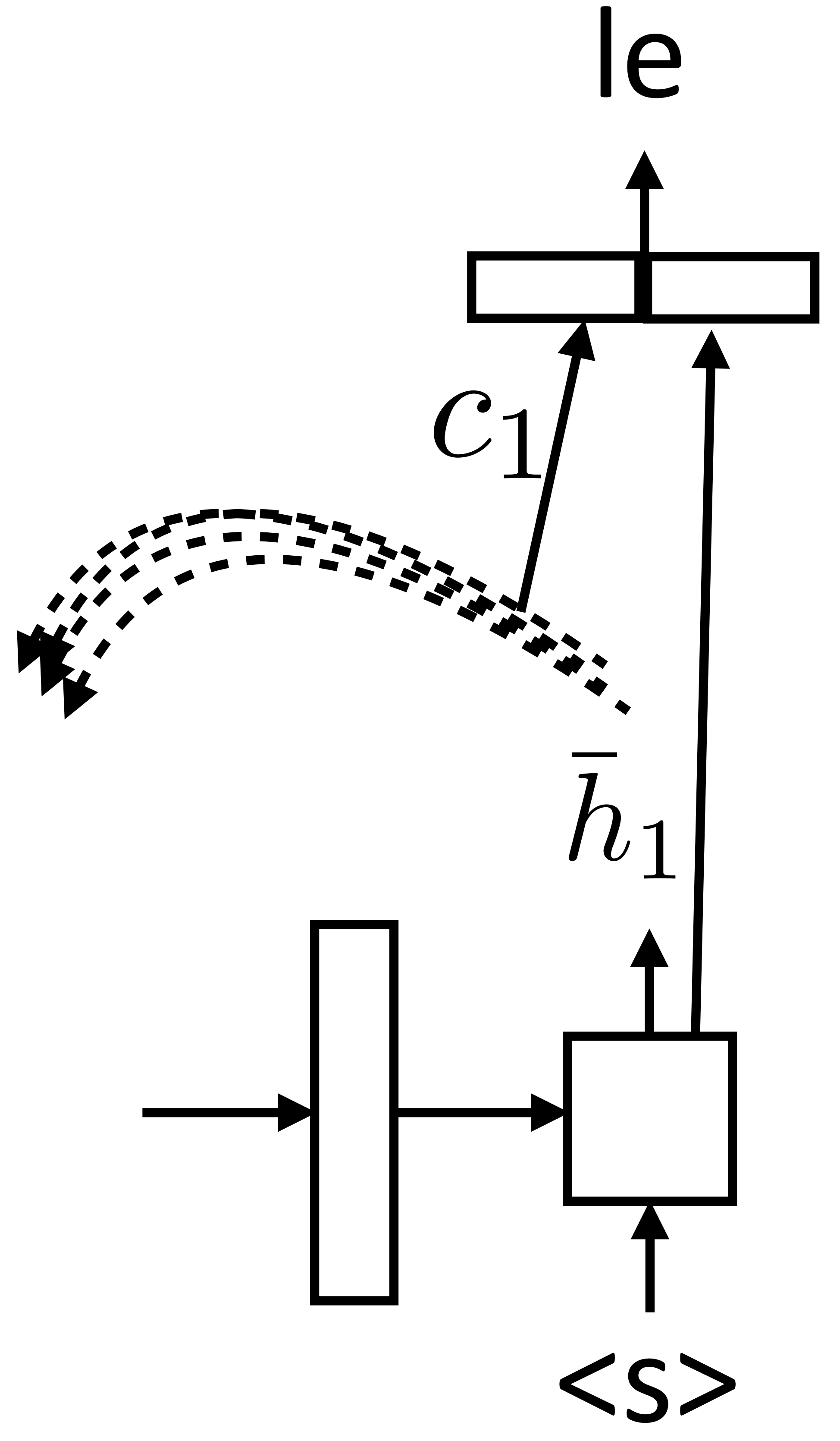
$$c_i = \sum_j \alpha_{ij} h_j$$

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

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

Luong et al. (2015)

Attention



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

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

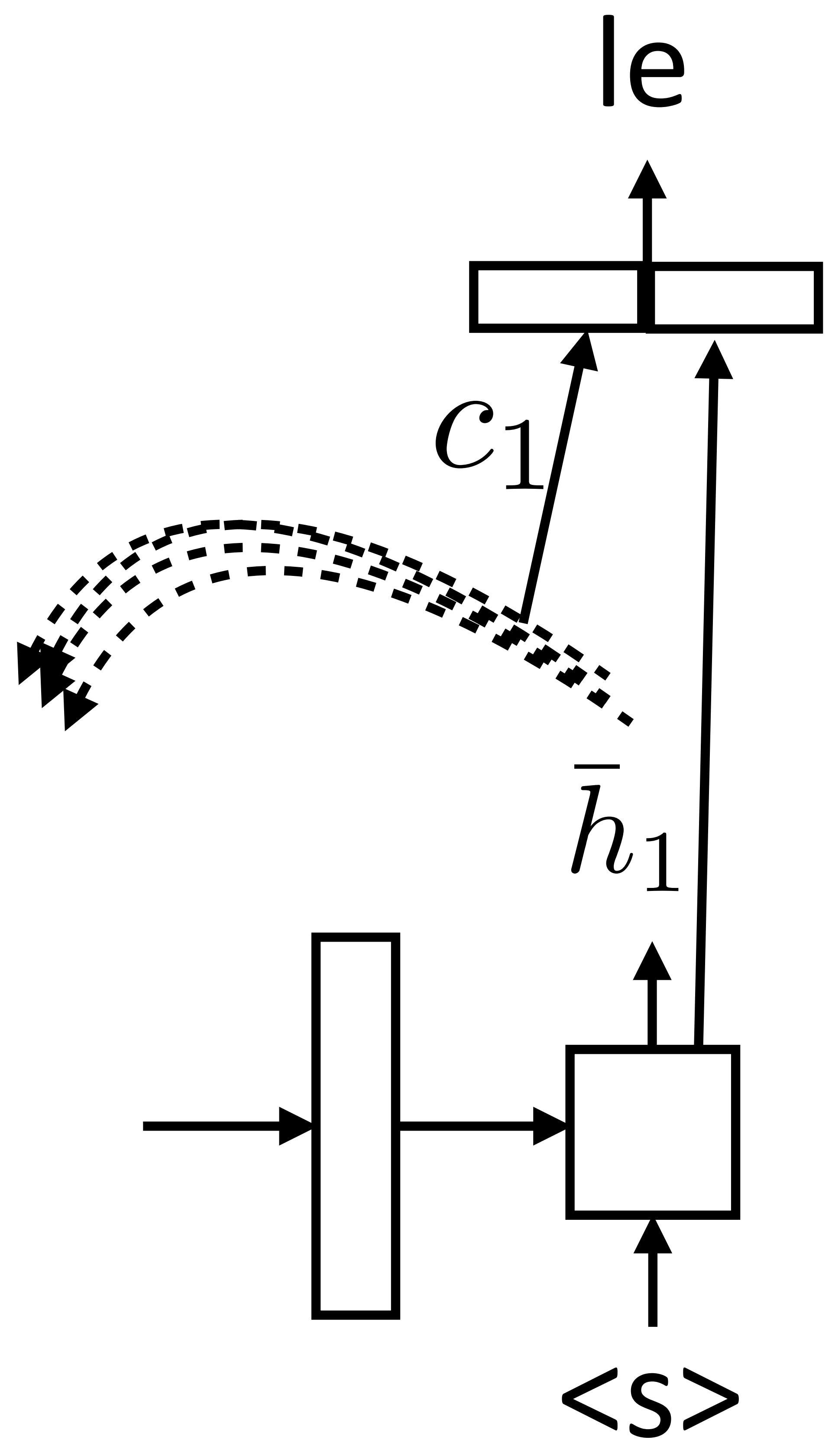
$$e_{ij} = f(\bar{h}_i, h_j)$$

$$f(\bar{h}_i, h_j) = \tanh(W[\bar{h}_i, h_j])$$

- Bahdanau+ (2014): additive

Luong et al. (2015)

Attention



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

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

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

$$f(\bar{h}_i, h_j) = \tanh(W[\bar{h}_i, h_j])$$

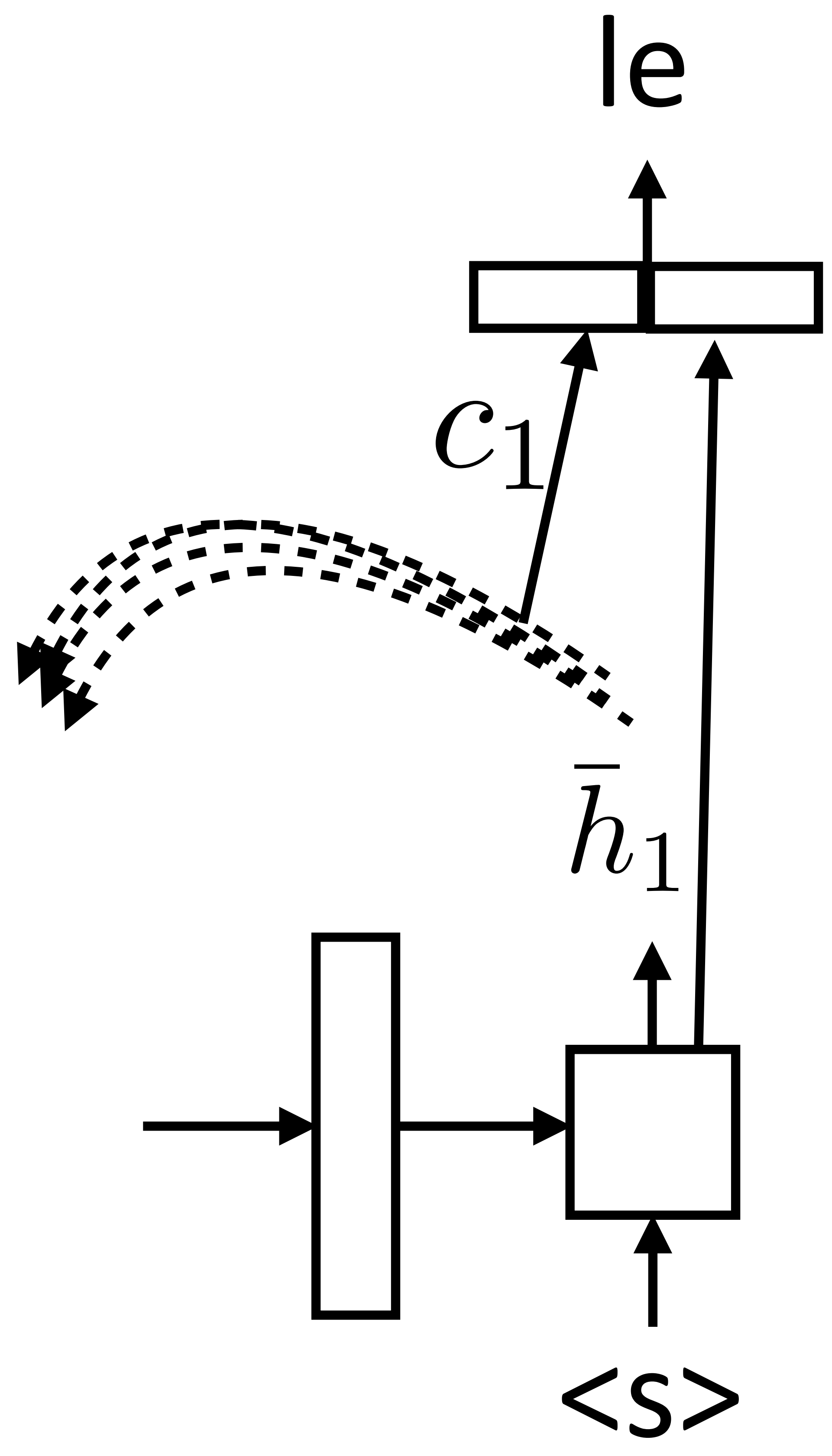
- Bahdanau+ (2014): additive

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

- Luong+ (2015): dot product

Luong et al. (2015)

Attention



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

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

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

$$f(\bar{h}_i, h_j) = \tanh(W[\bar{h}_i, h_j])$$

- Bahdanau+ (2014): additive

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

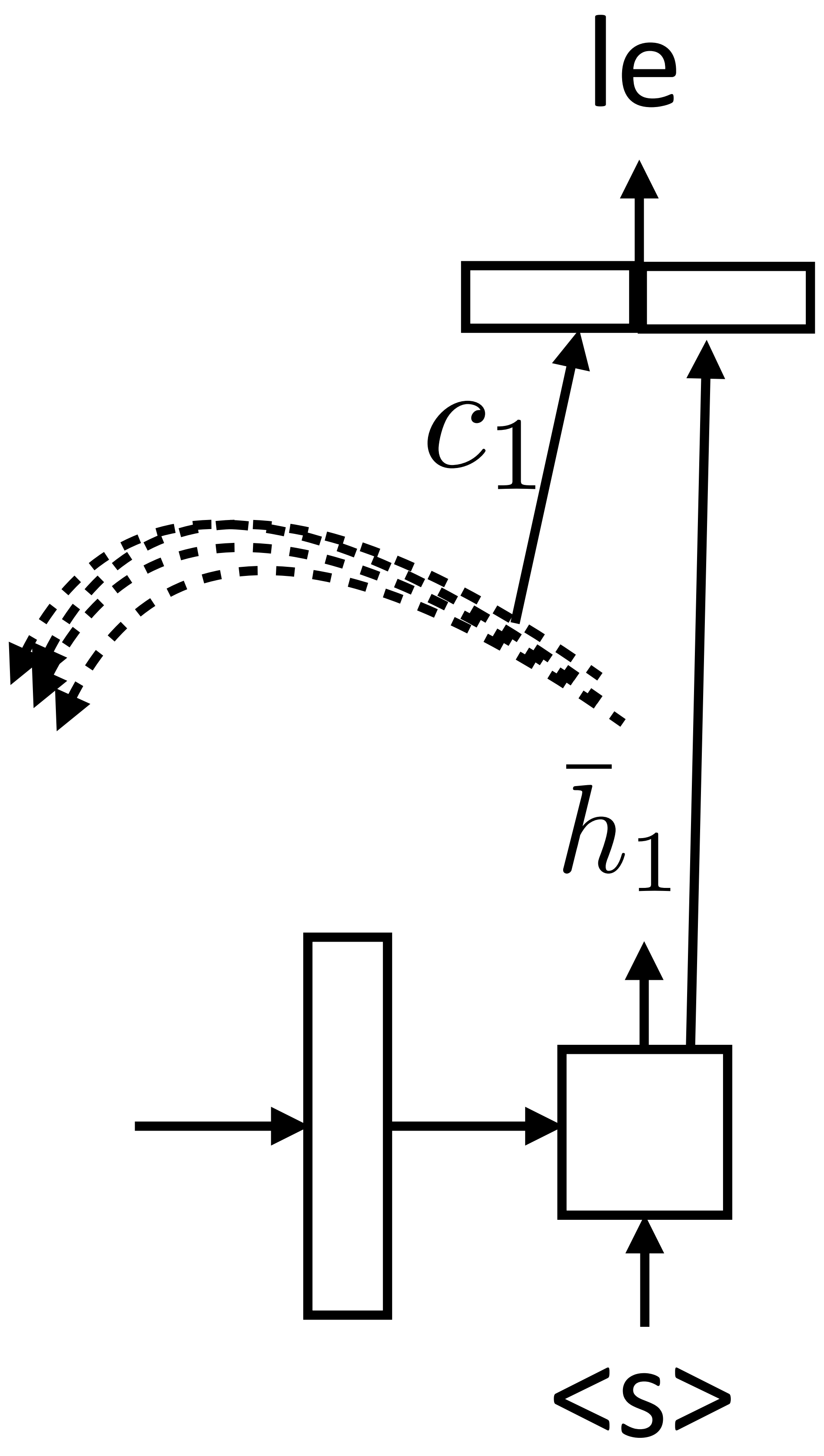
- Luong+ (2015): dot product

$$f(\bar{h}_i, h_j) = \bar{h}_i^\top W h_j$$

- Luong+ (2015): bilinear

Luong et al. (2015)

Attention



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

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

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

$$f(\bar{h}_i, h_j) = \tanh(W[\bar{h}_i, h_j])$$

- Bahdanau+ (2014): additive

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

- Luong+ (2015): dot product

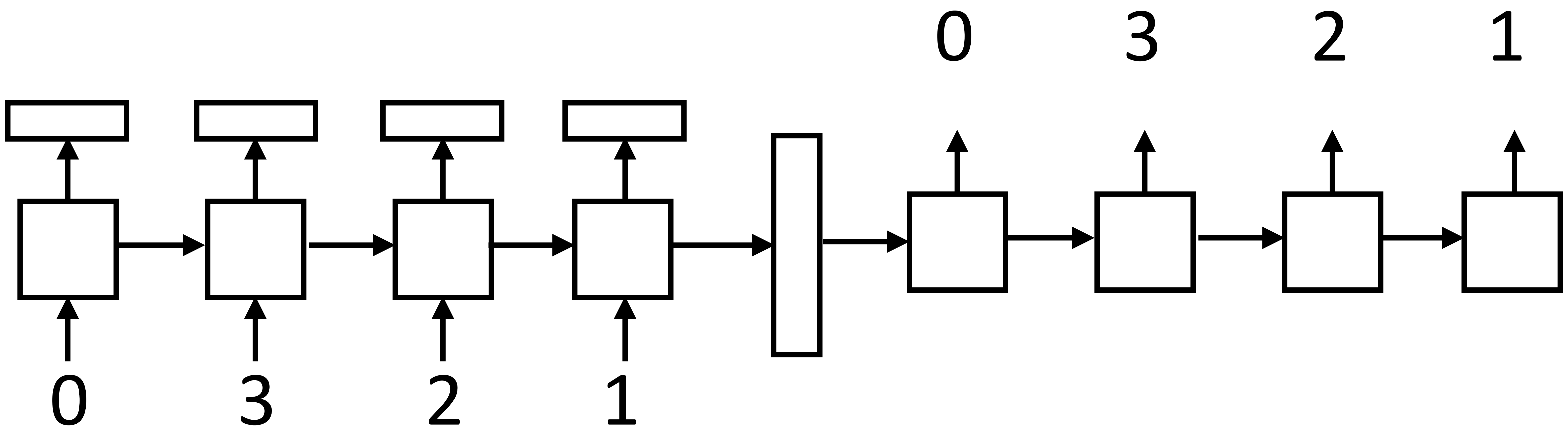
$$f(\bar{h}_i, h_j) = \bar{h}_i^\top W h_j$$

- Luong+ (2015): bilinear

- Note that this all uses outputs of hidden layers

Luong et al. (2015)

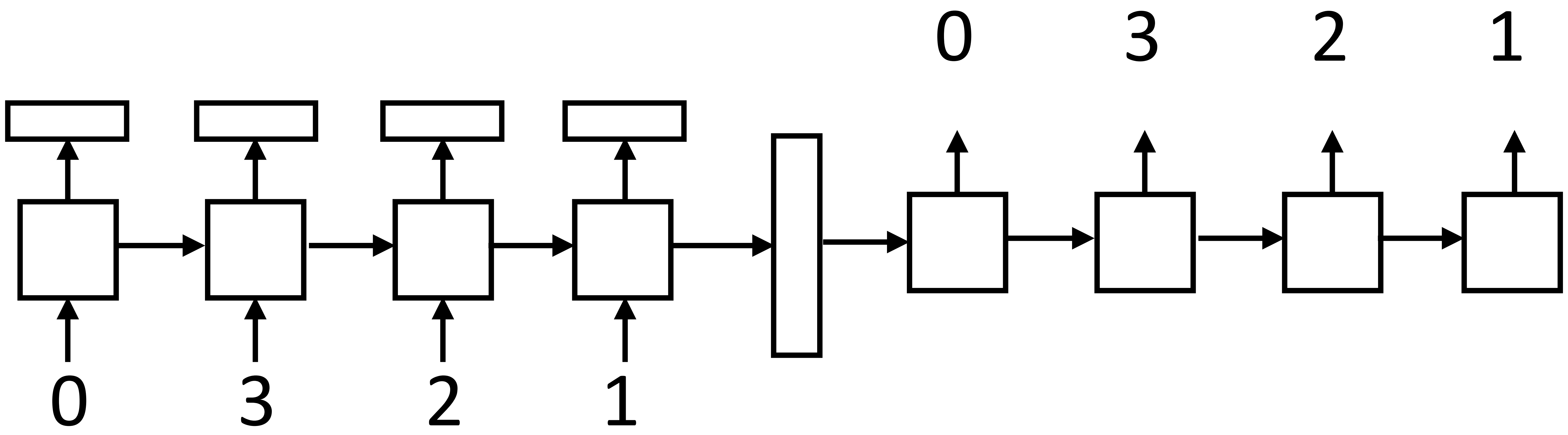
What can attention do?



Luong et al. (2015)

What can attention do?

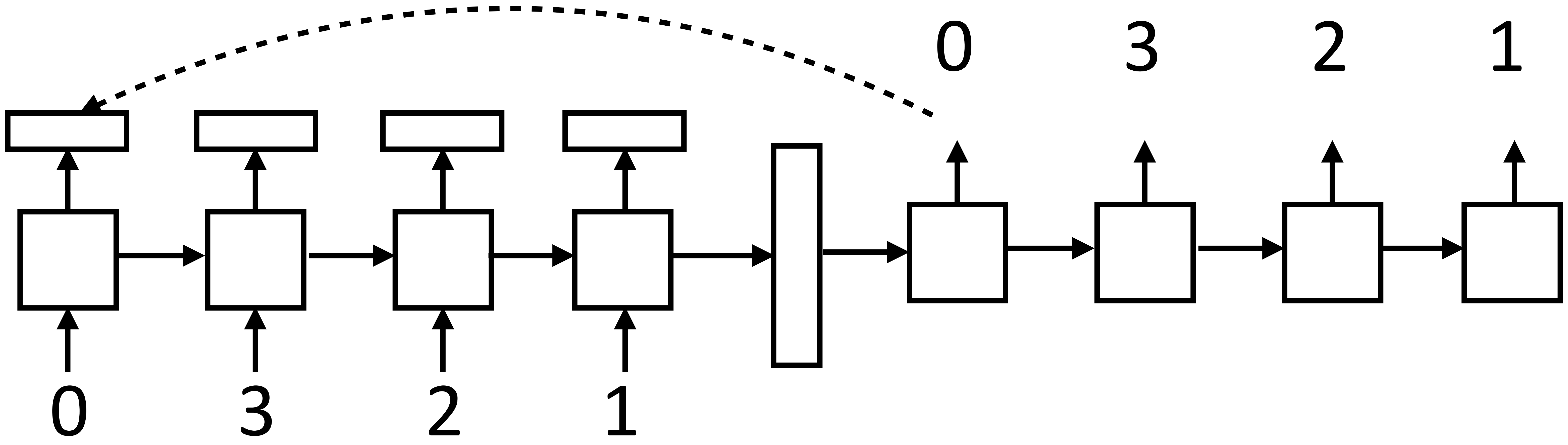
- Learning to copy — how might this work?



Luong et al. (2015)

What can attention do?

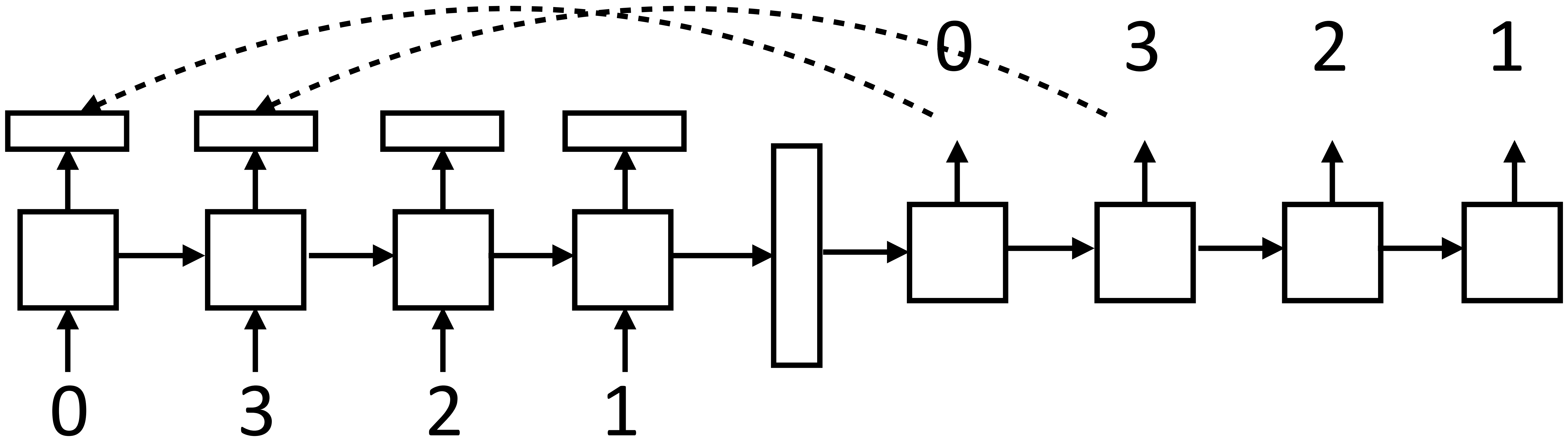
- Learning to copy — how might this work?



Luong et al. (2015)

What can attention do?

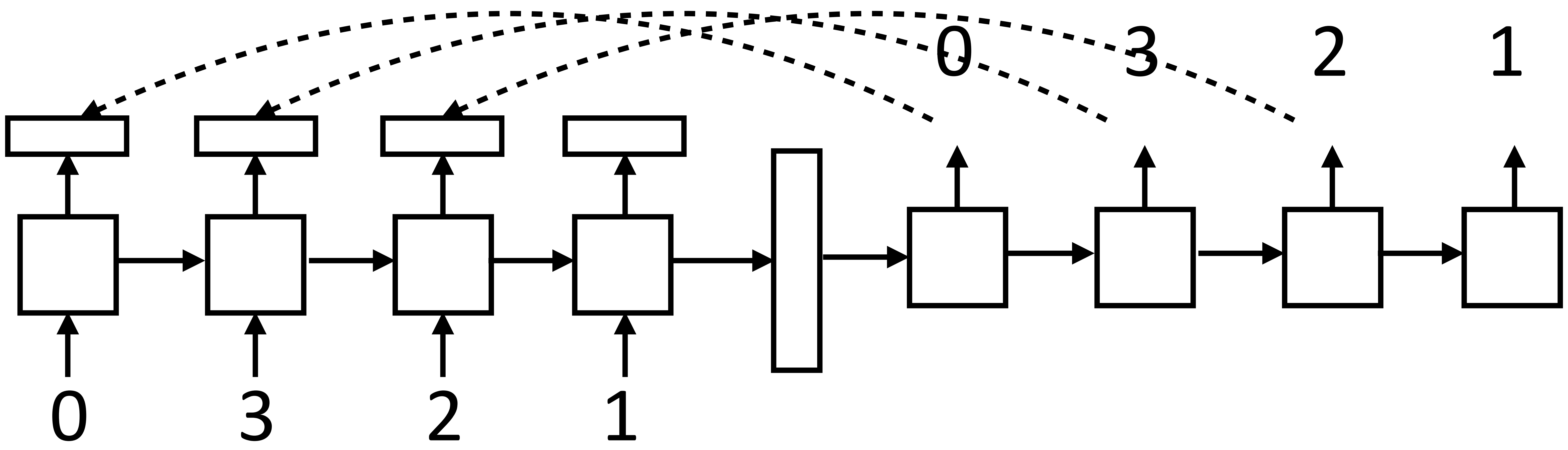
- Learning to copy — how might this work?



Luong et al. (2015)

What can attention do?

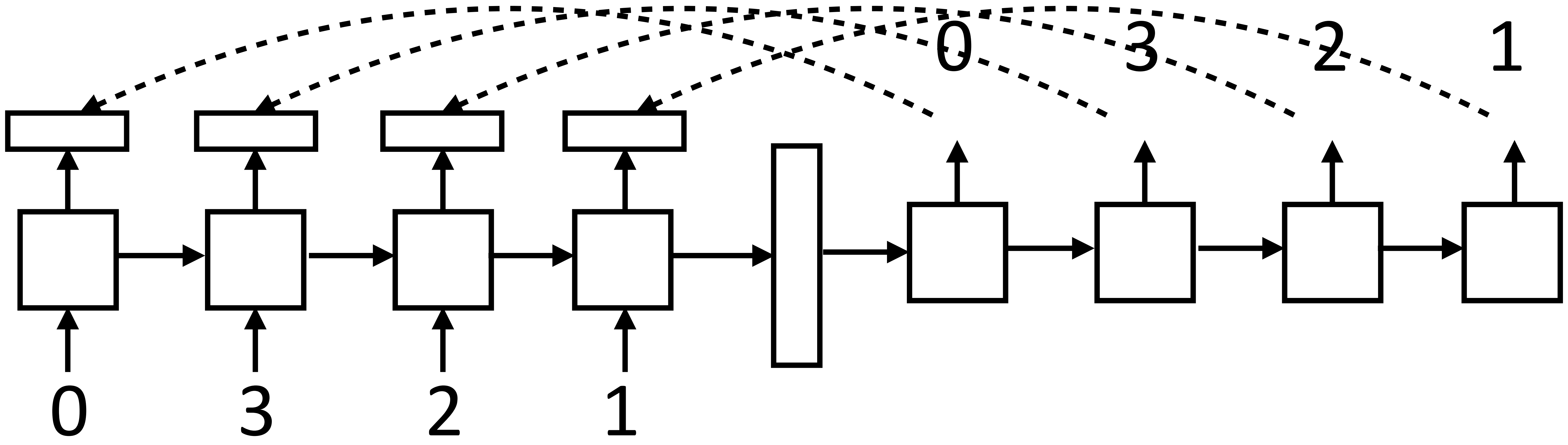
- Learning to copy — how might this work?



Luong et al. (2015)

What can attention do?

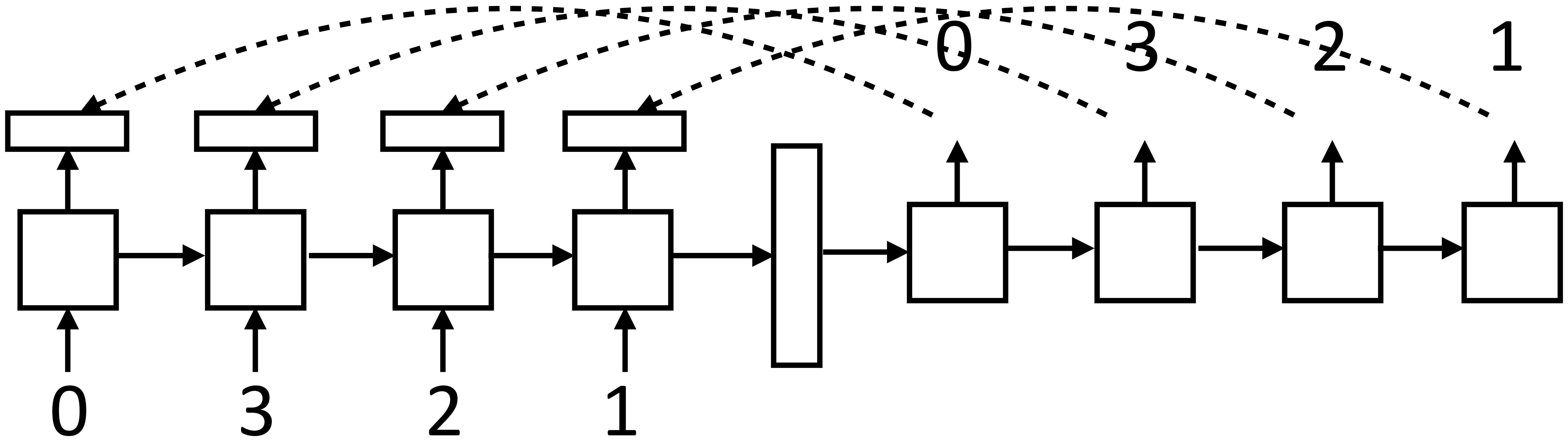
- Learning to copy — how might this work?



Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?

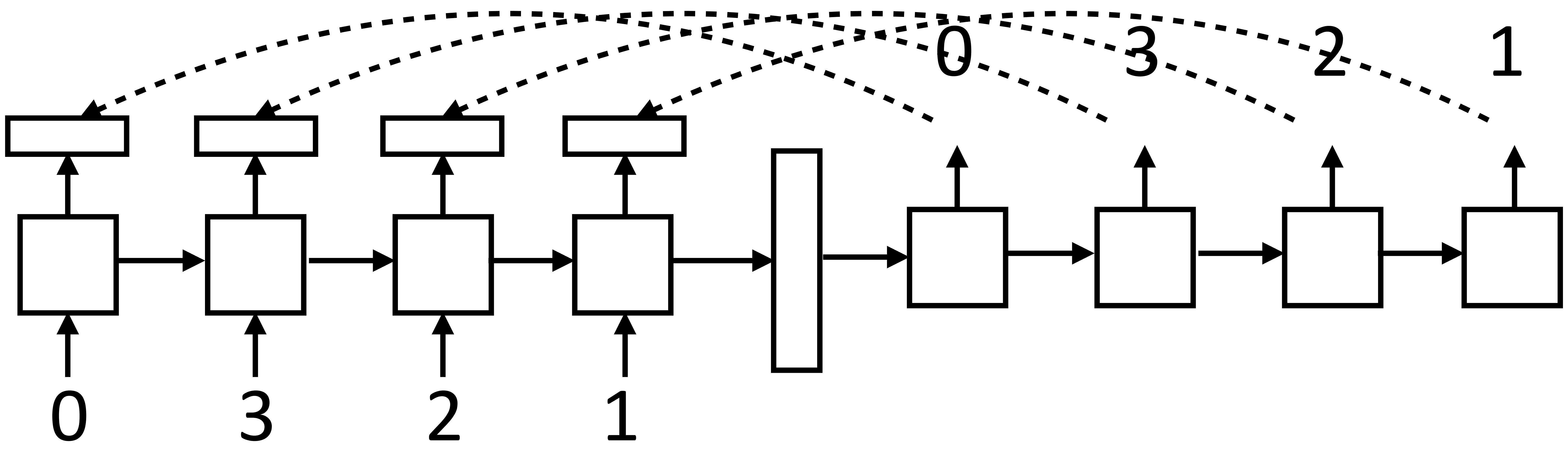


- LSTM can learn to count with the right weight matrix

Luong et al. (2015)

What can attention do?

- Learning to copy — how might this work?

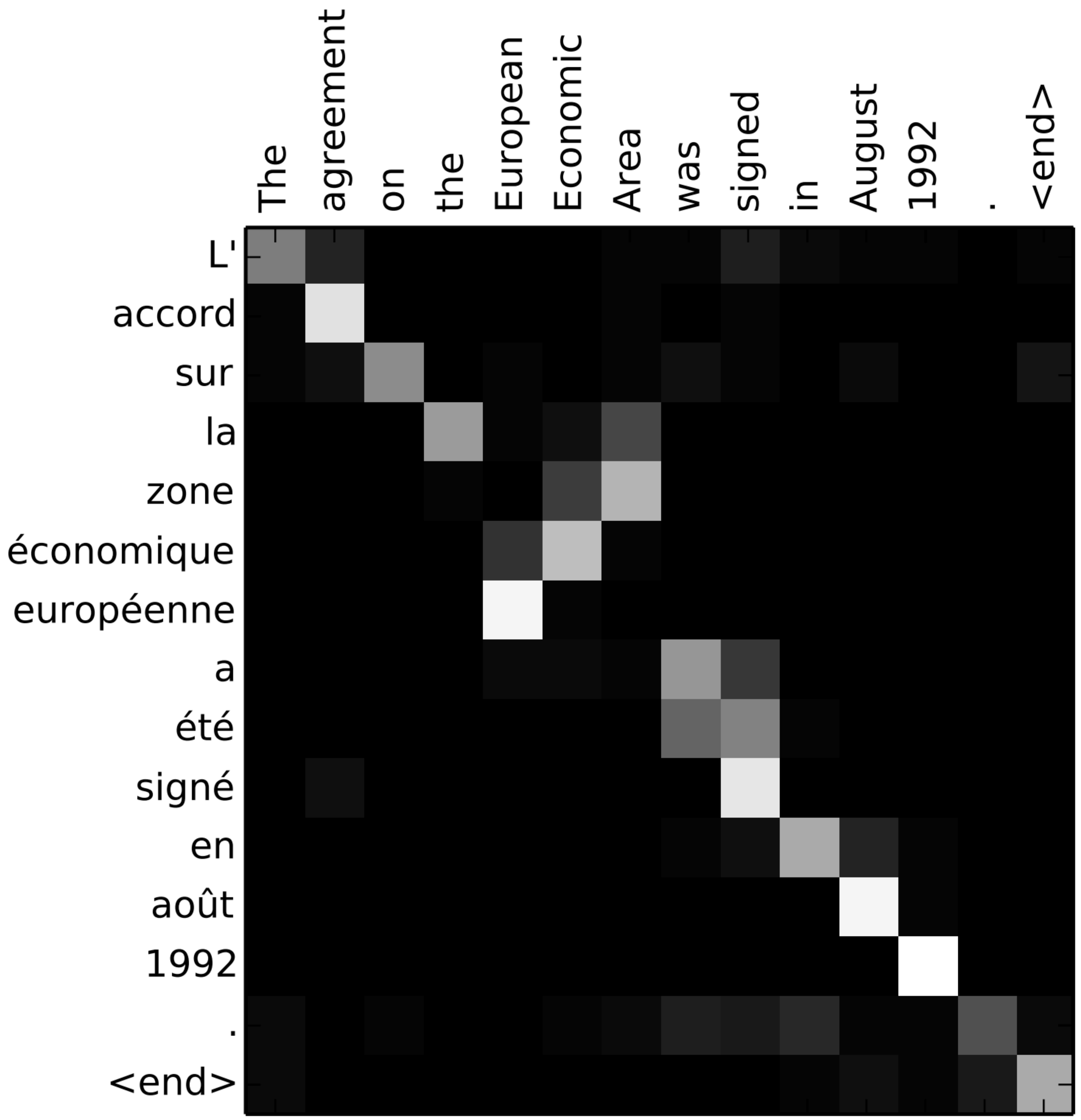


- LSTM can learn to count with the right weight matrix

- This is effectively position-based addressing

Luong et al. (2015)

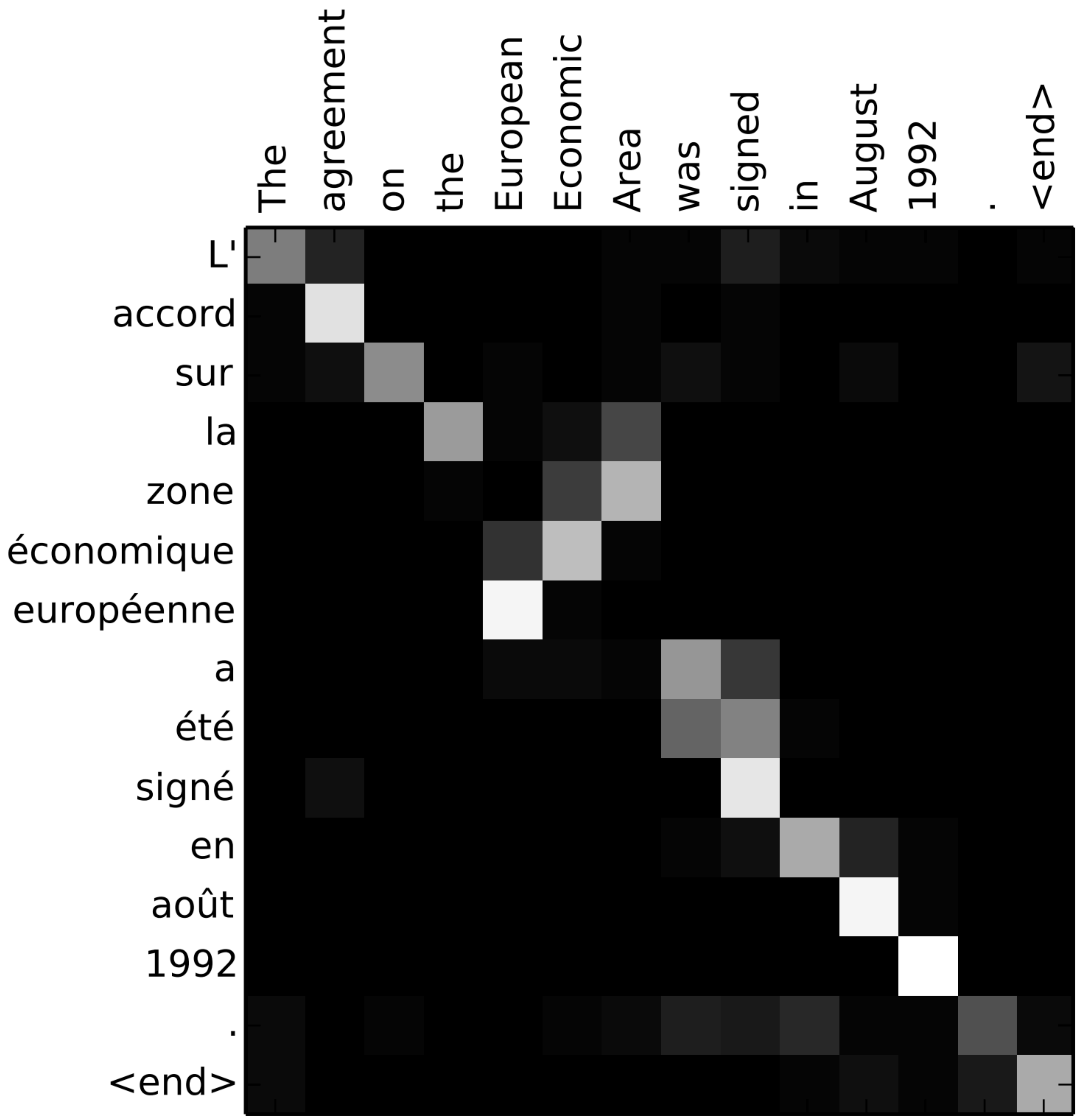
Attention



The
agreement
on
the
European
Economic
Area
was
signed
in
August
1992
.
<end>
L'
accord
sur
la
zone
économique
européenne
a
été
signé
en
août
1992
.
<end>

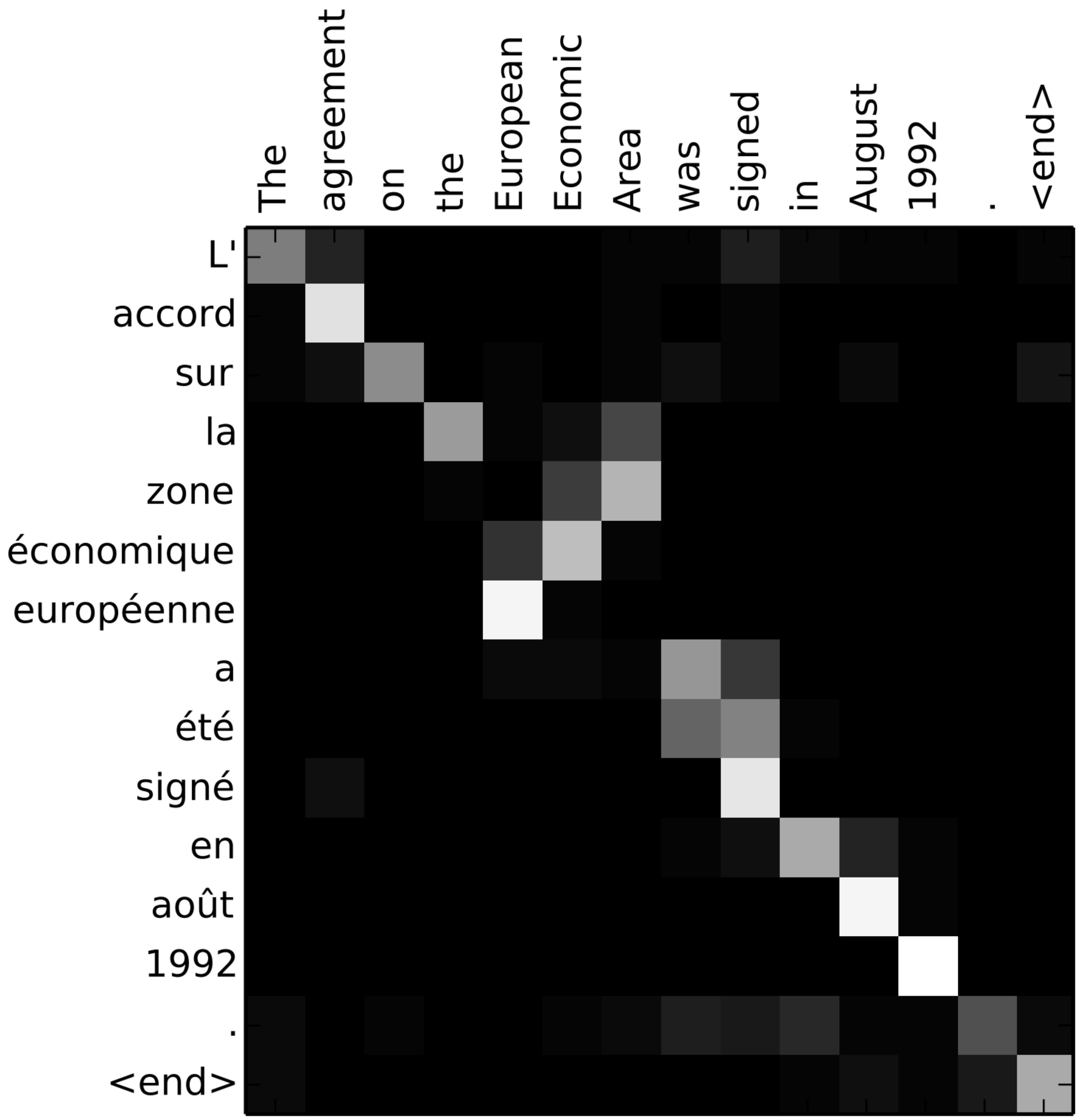
Attention

- Encoder hidden states capture contextual source word identity



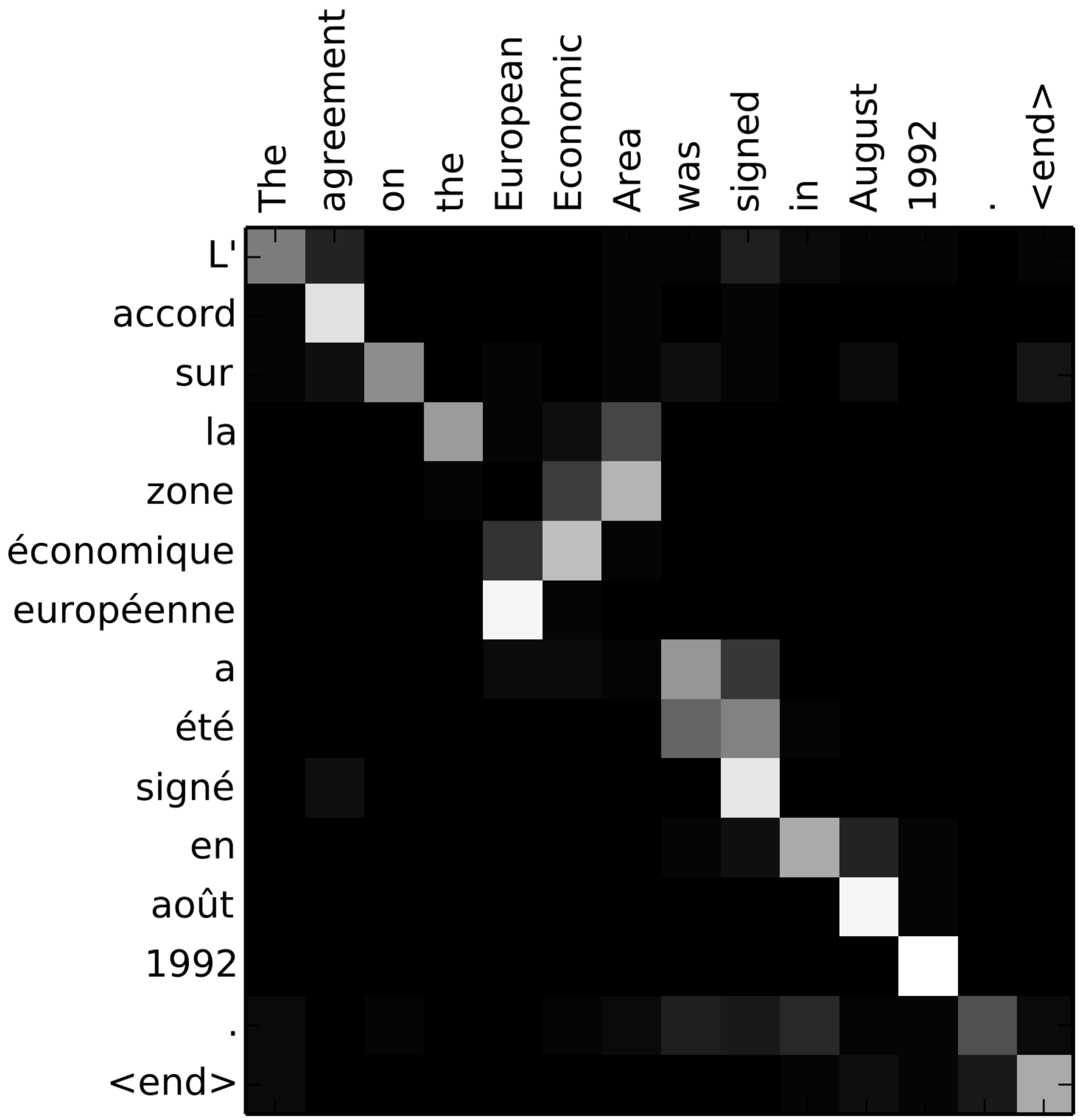
Attention

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

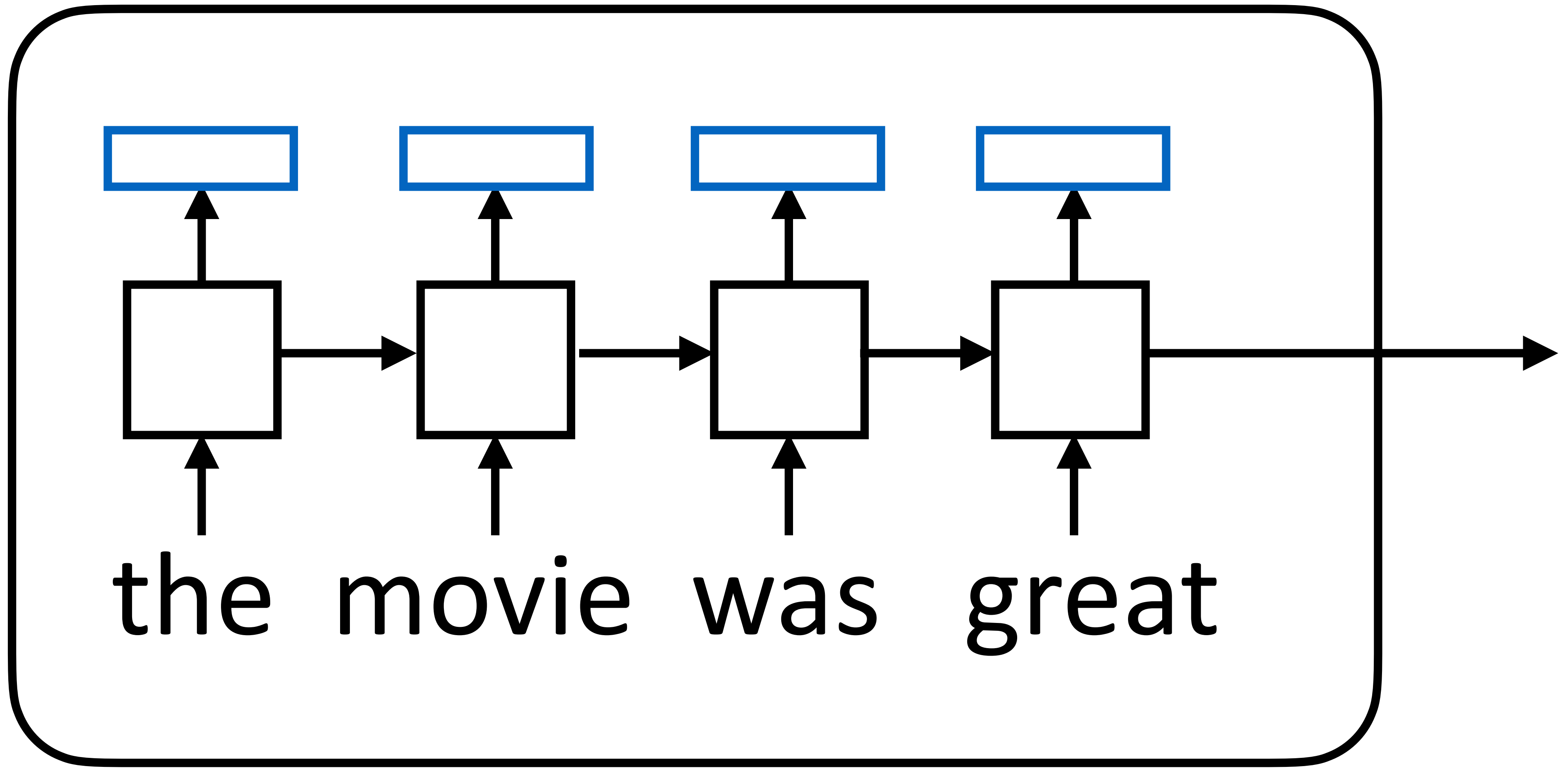


Attention

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



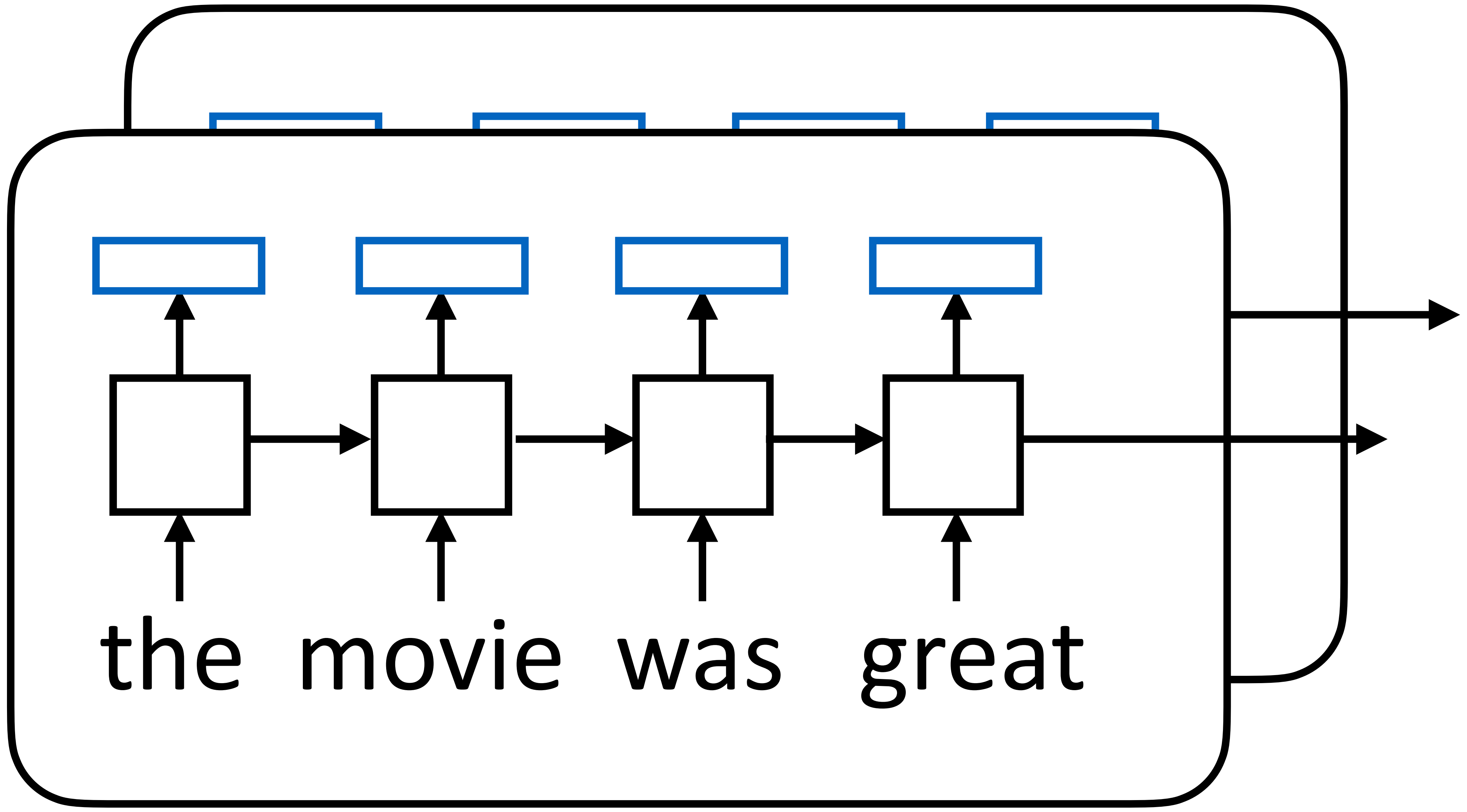
Batching Attention



Luong et al. (2015)

Batching Attention

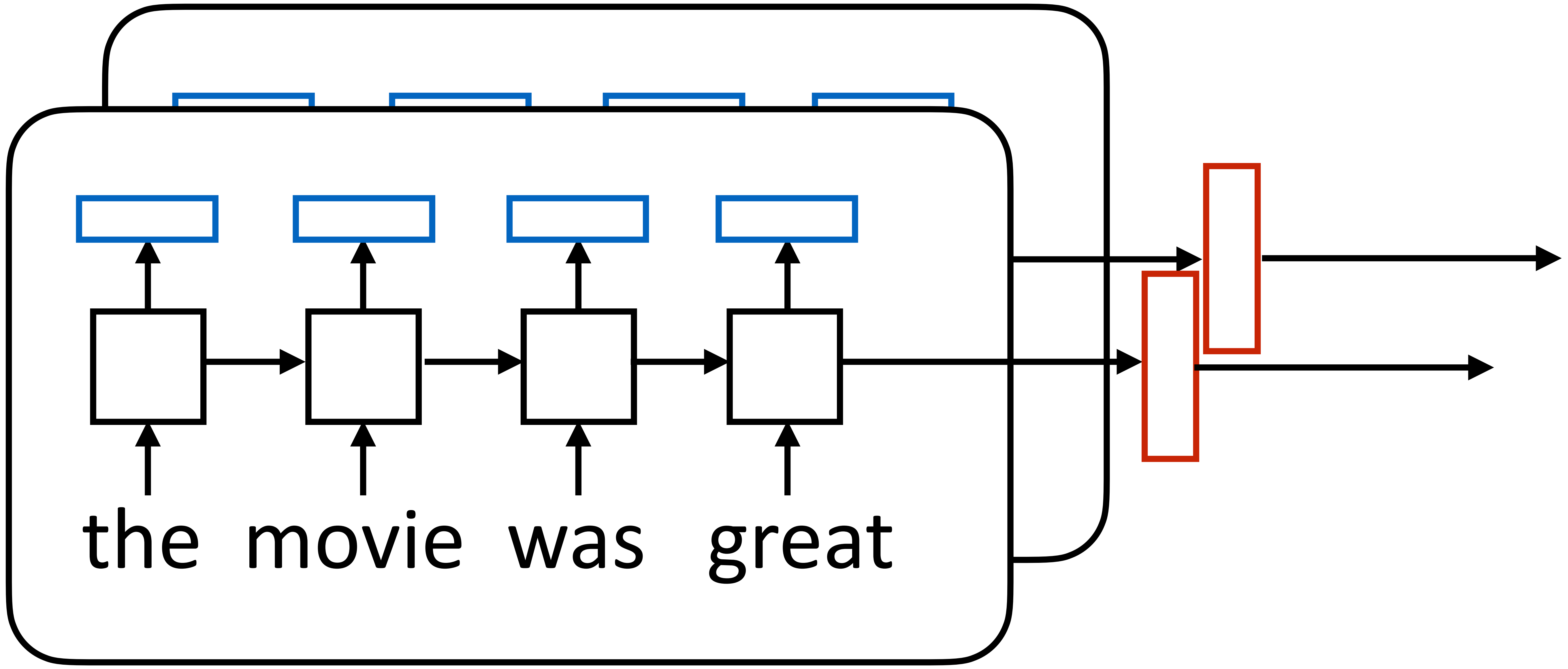
token outputs: batch size x sentence length x dimension



Luong et al. (2015)

Batching Attention

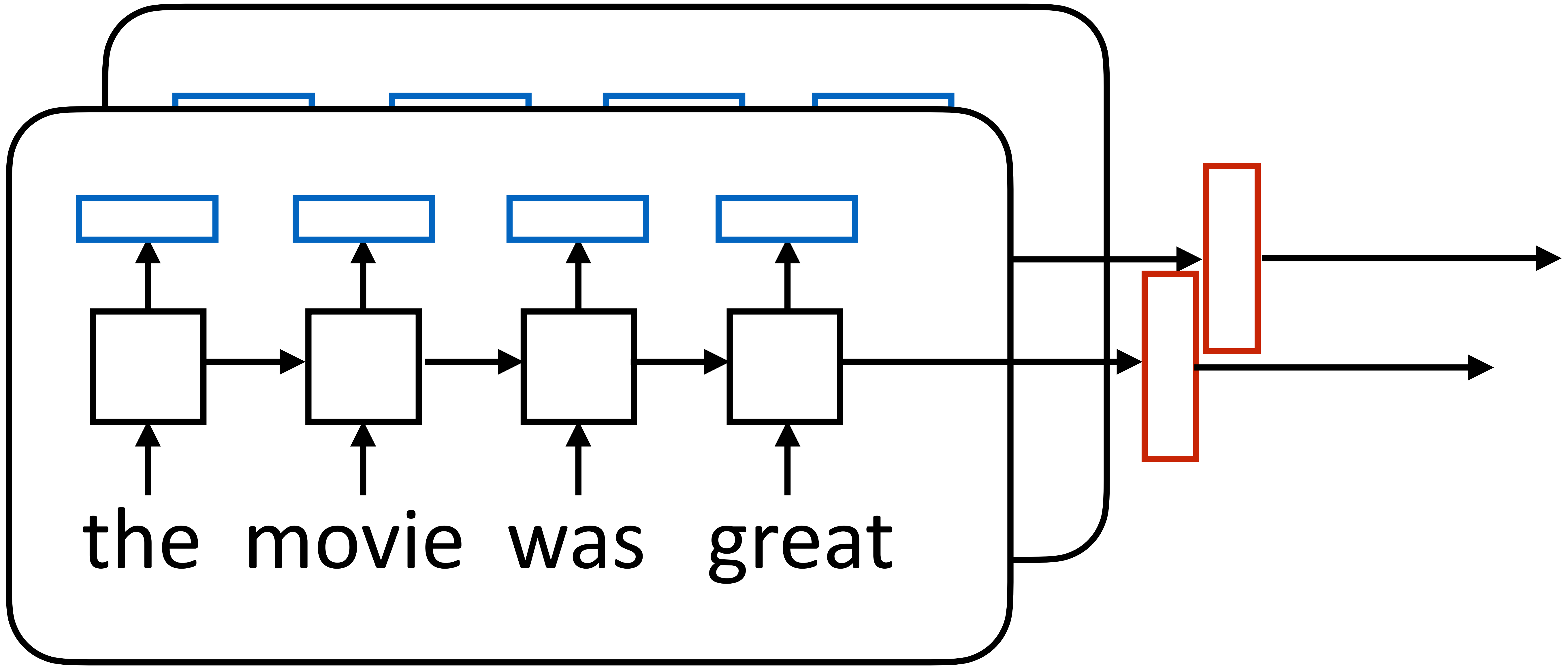
token outputs: batch size x sentence length x dimension



Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension

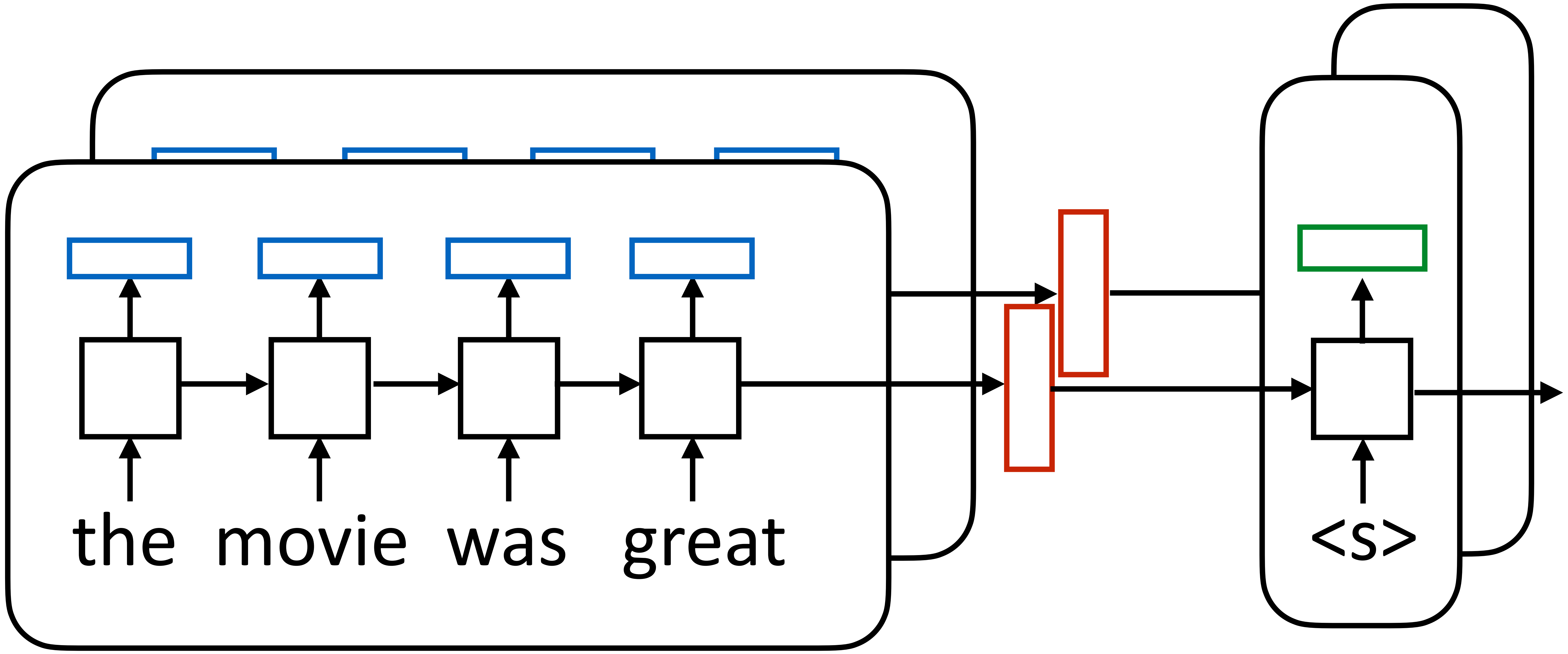


sentence outputs:
batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension

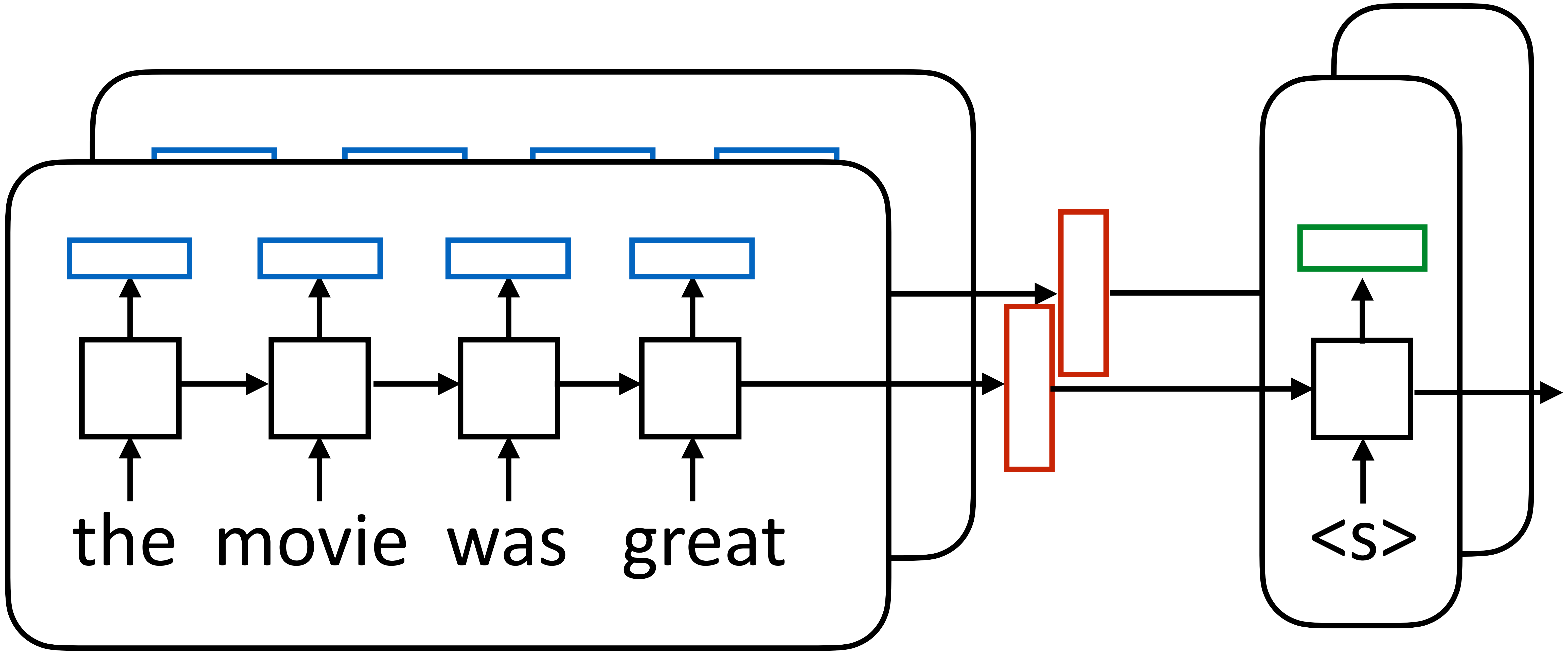


sentence outputs:
batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



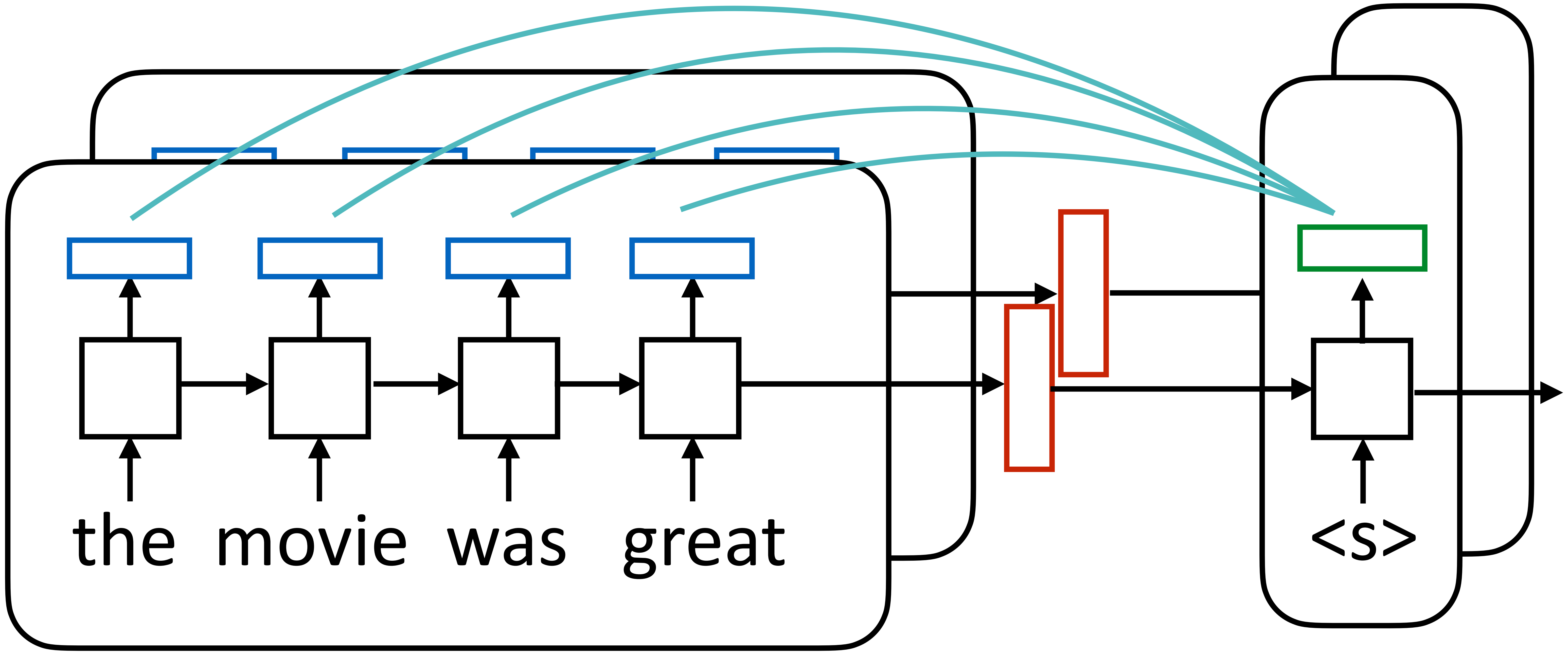
hidden state: batch size x hidden size

sentence outputs:
batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



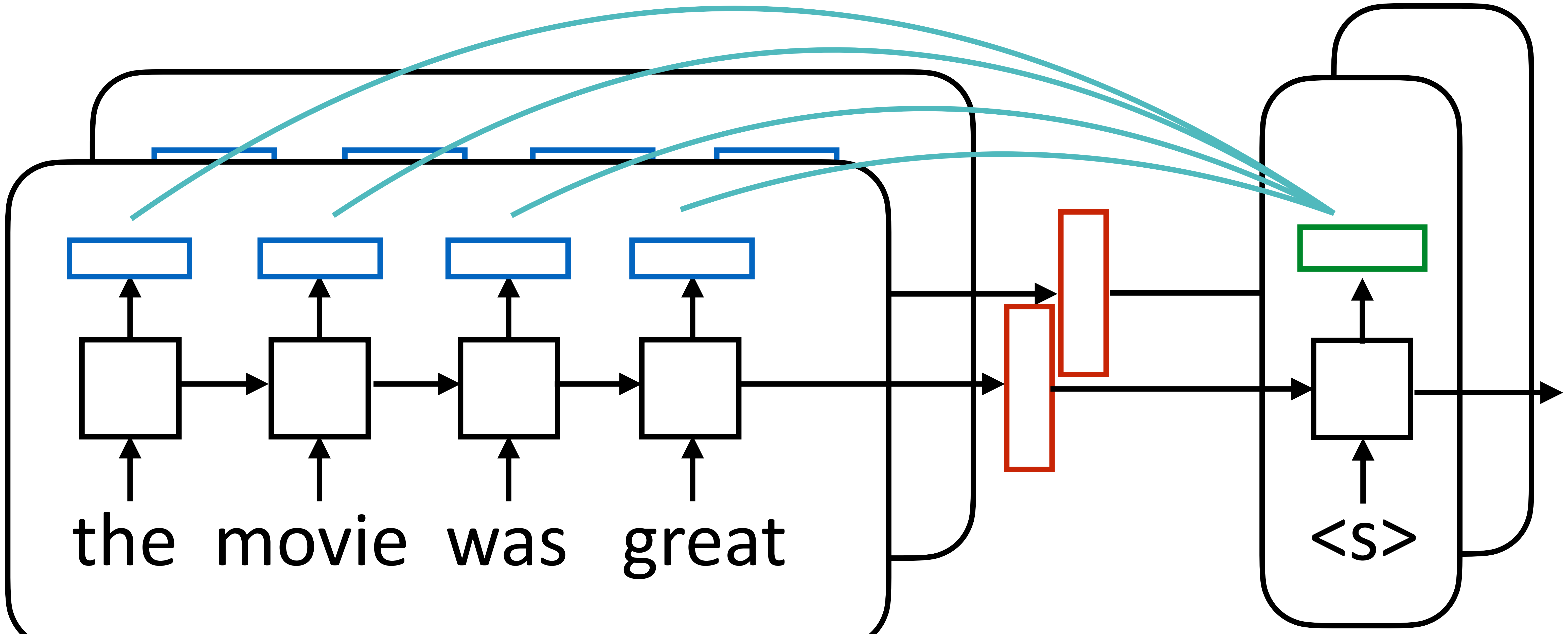
hidden state: batch size x hidden size

sentence outputs: batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



hidden state: batch size x hidden size

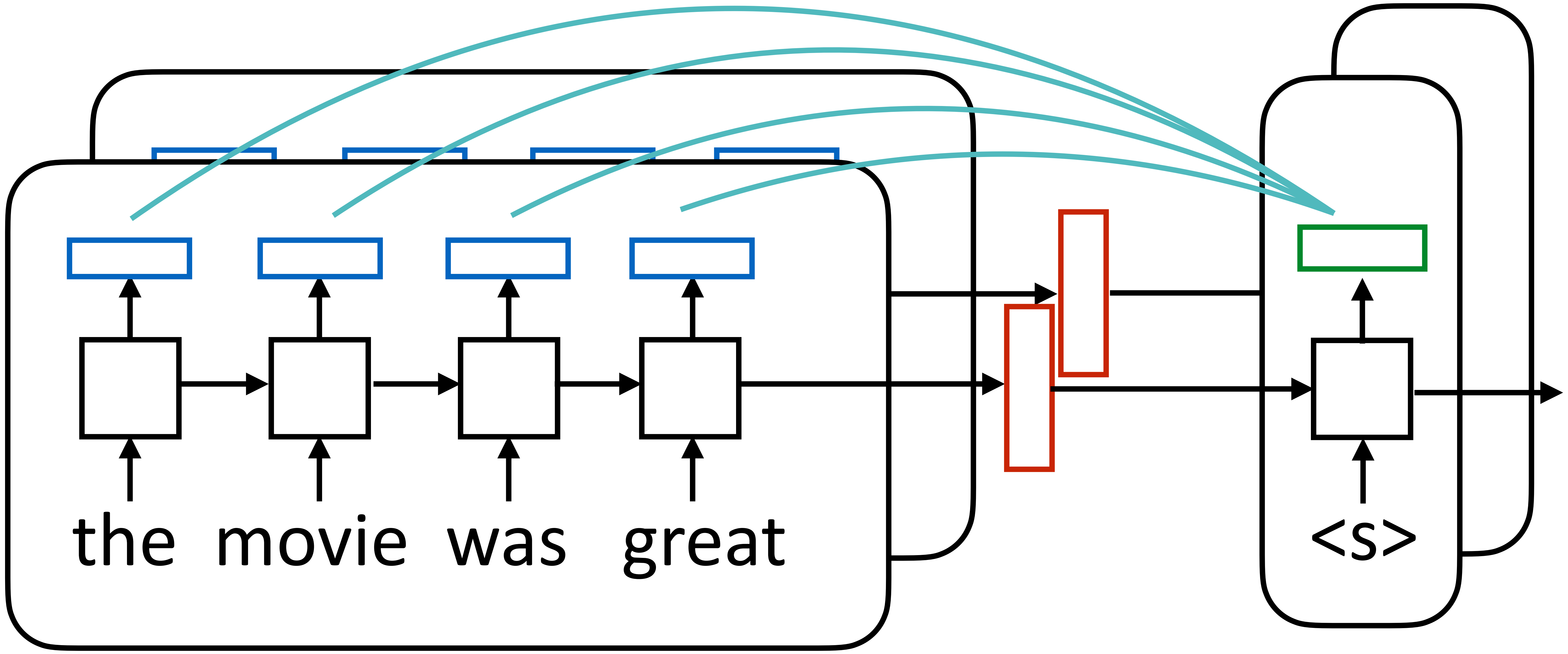
$$e_{ij} = f(\bar{h}_i, h_j)$$

sentence outputs:
batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



hidden state: batch size x hidden size

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

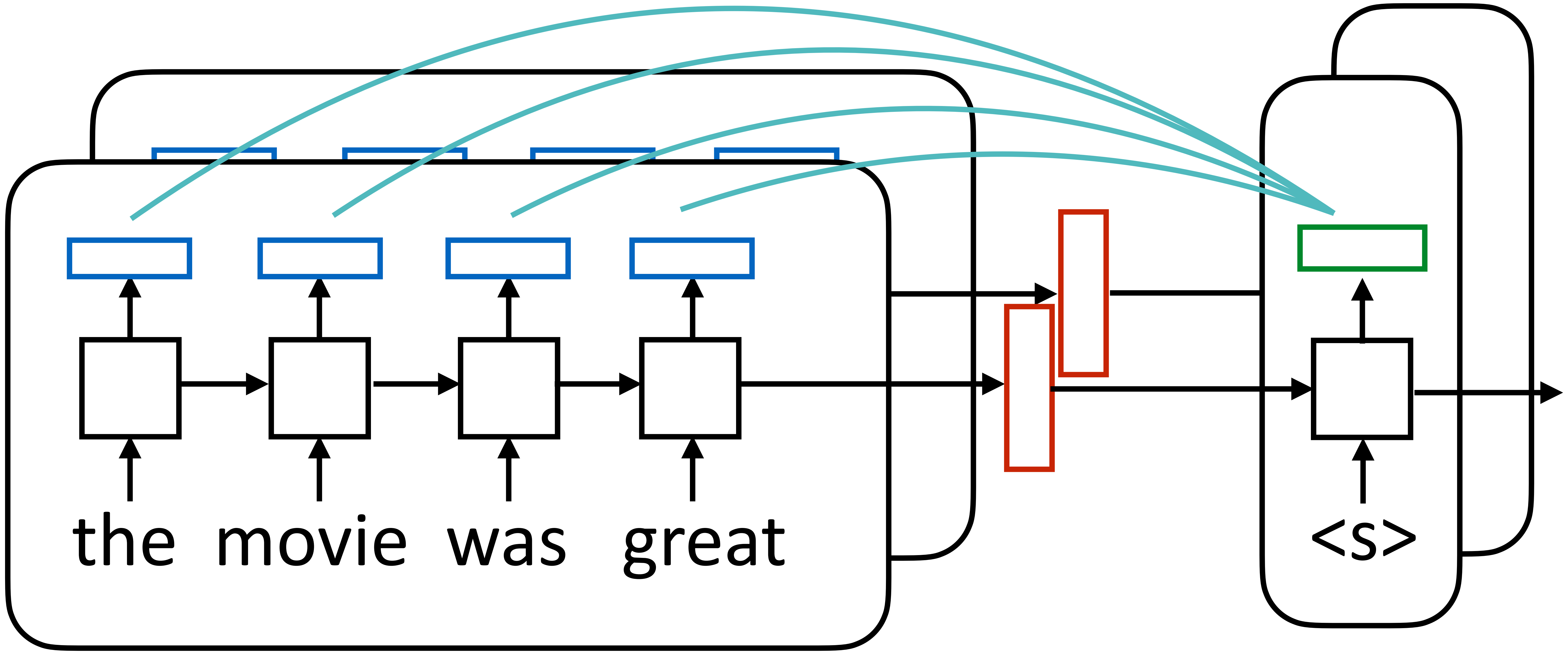
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

sentence outputs:
batch size x hidden size

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



hidden state: batch size x hidden size

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

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

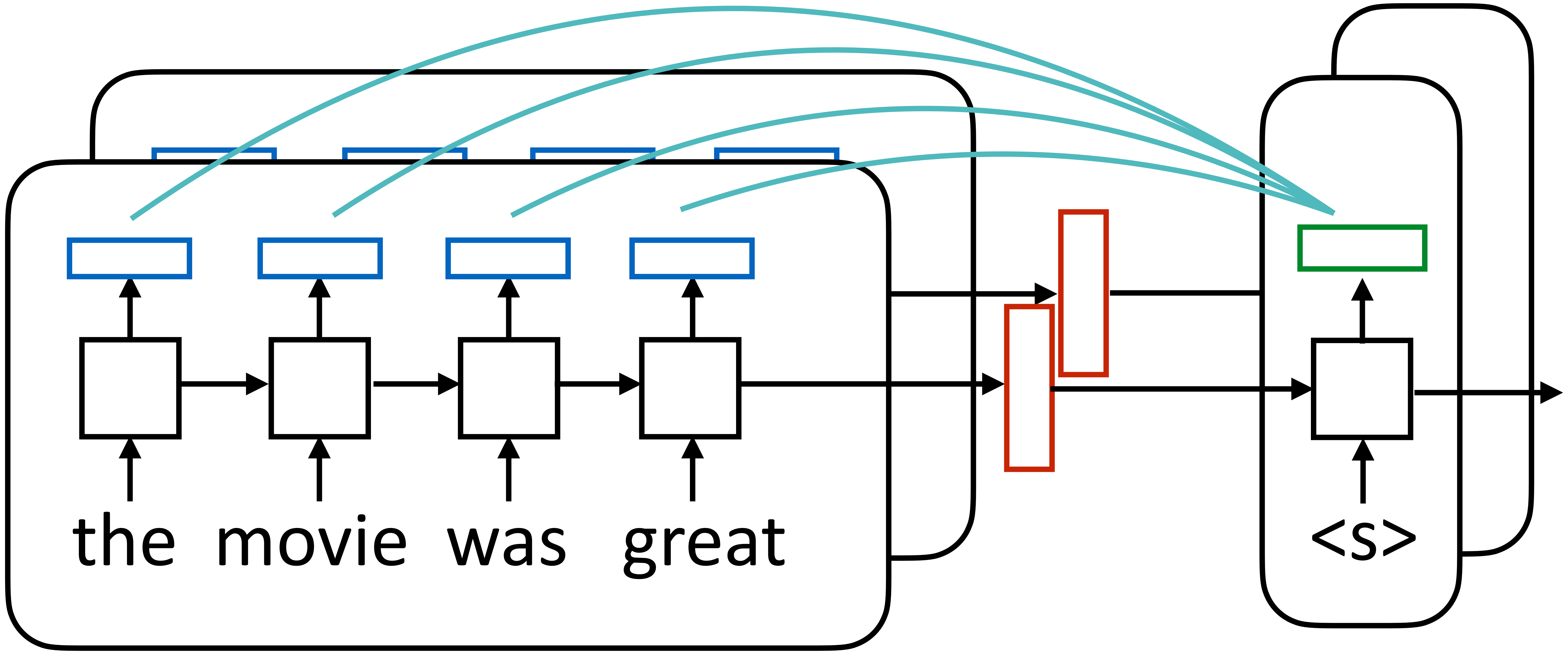
sentence outputs: batch size x hidden size

attention scores = batch size x sentence length

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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

attention scores = batch size x sentence length

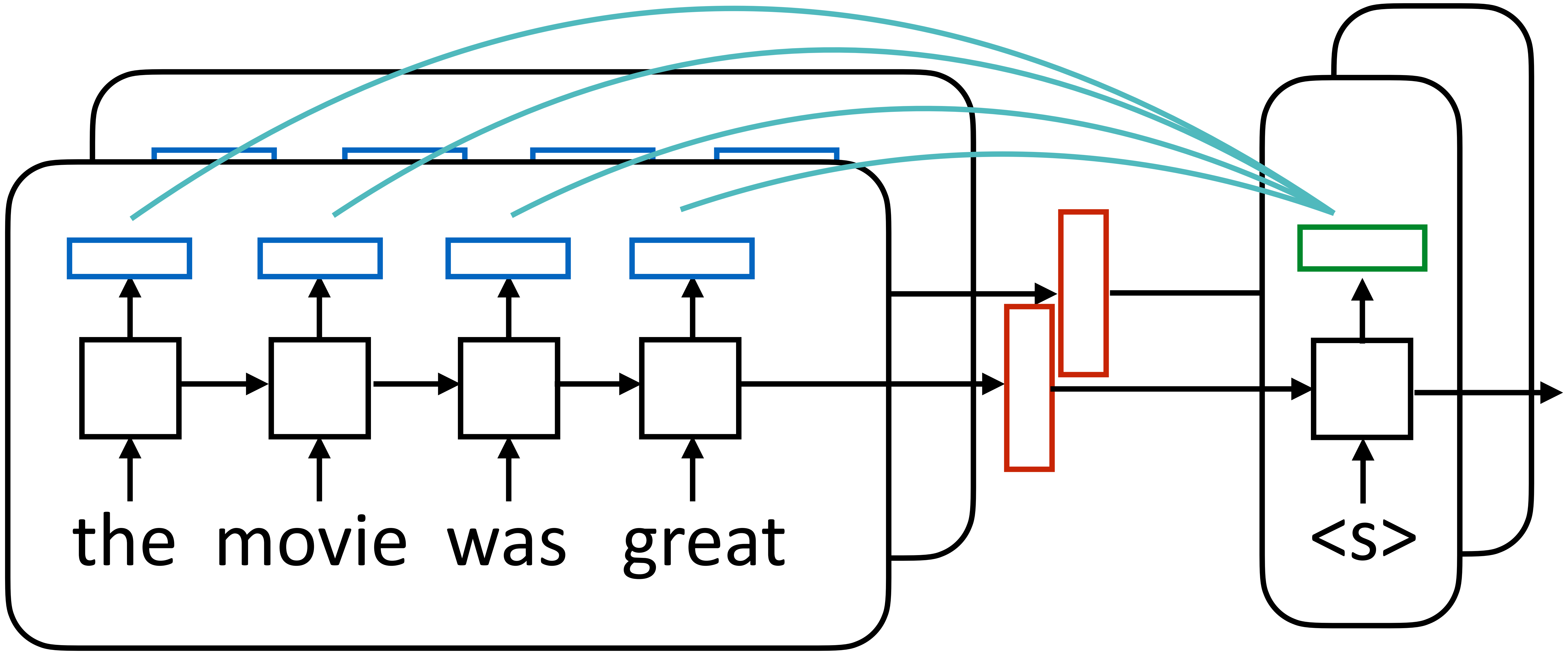
c = batch size x hidden size

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

Luong et al. (2015)

Batching Attention

token outputs: batch size x sentence length x dimension



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

attention scores = batch size x sentence length

c = batch size x hidden size

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

- 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)
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)

- Summarization/headline generation: bigram recall from 11% -> 15%

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)
- 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

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

1

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

- 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)

Unknown Words

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

1

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

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

- 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

- Still can only generate from the vocabulary

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

Copying

en: The *ecotax* portico in *Pont-de-Buis* , . . . [truncated] . .

fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated]

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

Copying

en: The *ecotax* portico in *Pont-de-Buis* , . . . [truncated] . .

fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] .

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

en: The *ecotax* portico in *Pont-de-Buis* , . . . [truncated] . .

fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] .

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:

the
a
…
zebra

Pont-de-Buis
ecotax

Copying

en: The *ecotax* portico in *Pont-de-Buis* , . . . [truncated] . .

fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated]

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

the
a
…
zebra

Pont-de-Buis
ecotax

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

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

Copying

en: The ecotax portico in *Pont-de-Buis* , . . . [truncated] . .

fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] .

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

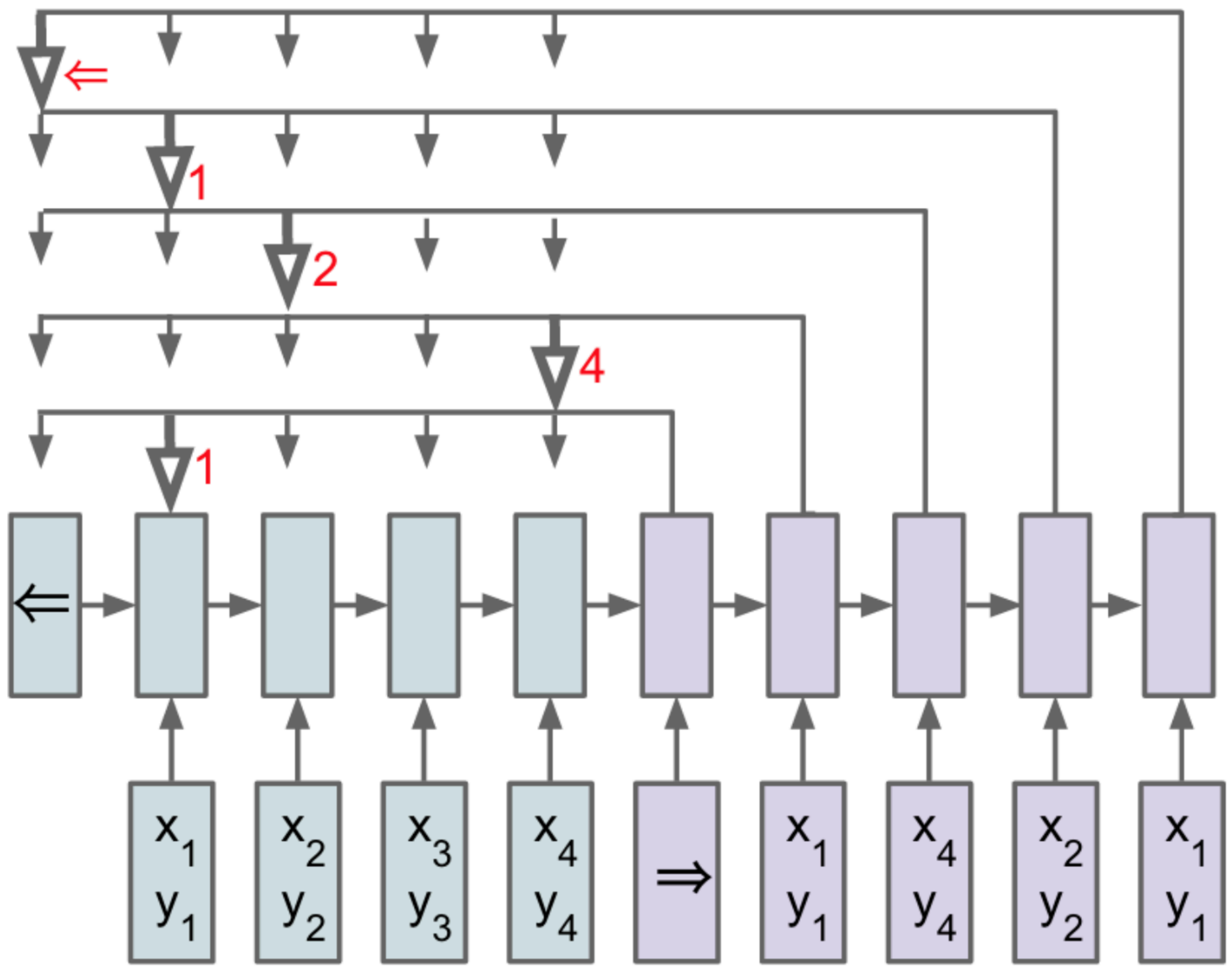
$$\left\{ \begin{array}{l} \text{the} \\ \text{a} \\ \ldots \\ \text{zebra} \\ \hline \text{Pont-de-Buis} \\ \text{ecotax} \end{array} \right\}$$

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

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

- Bilinear function of input representation + output hidden state

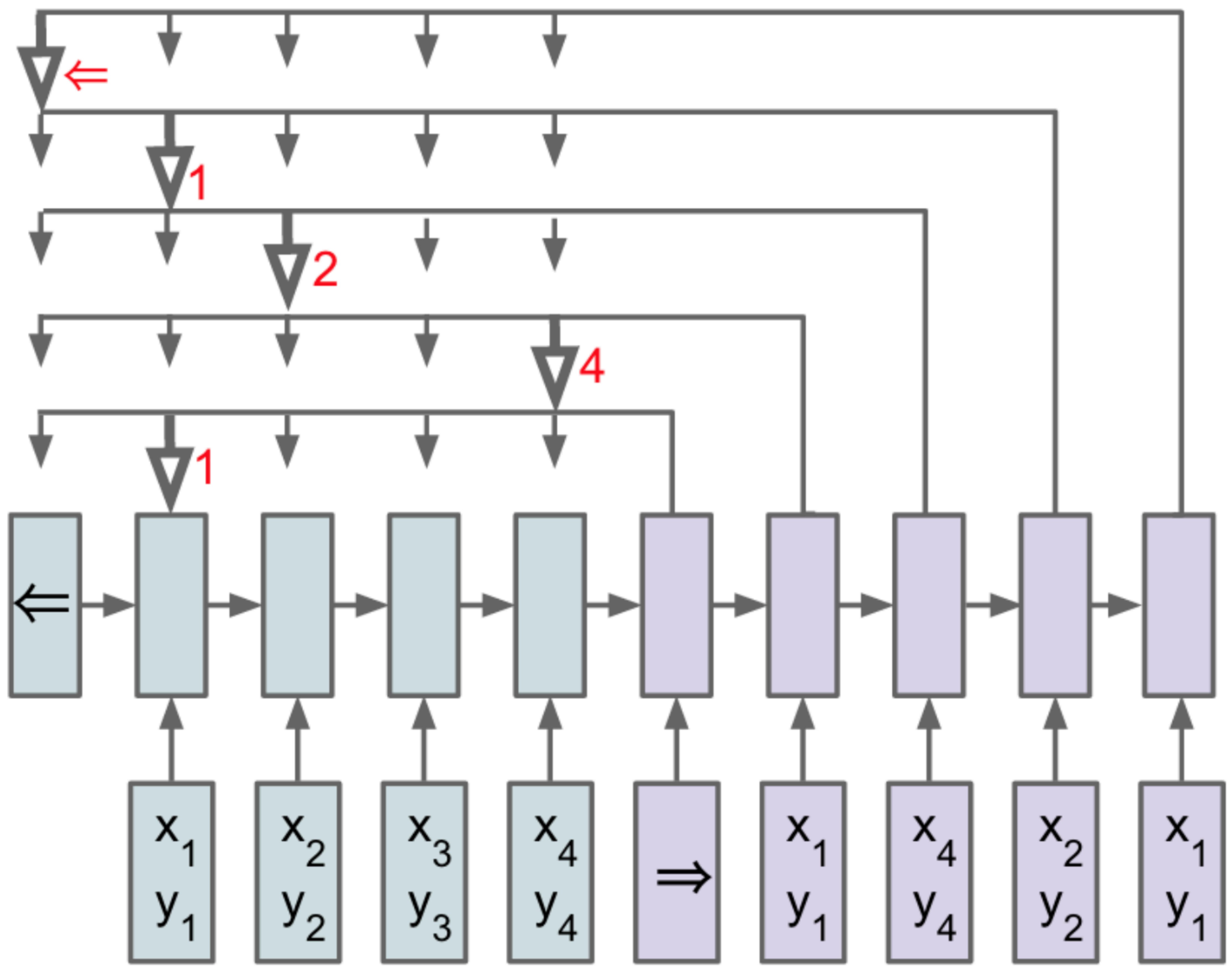
Pointer Networks



Vinyals et al. (2015)

Pointer Networks

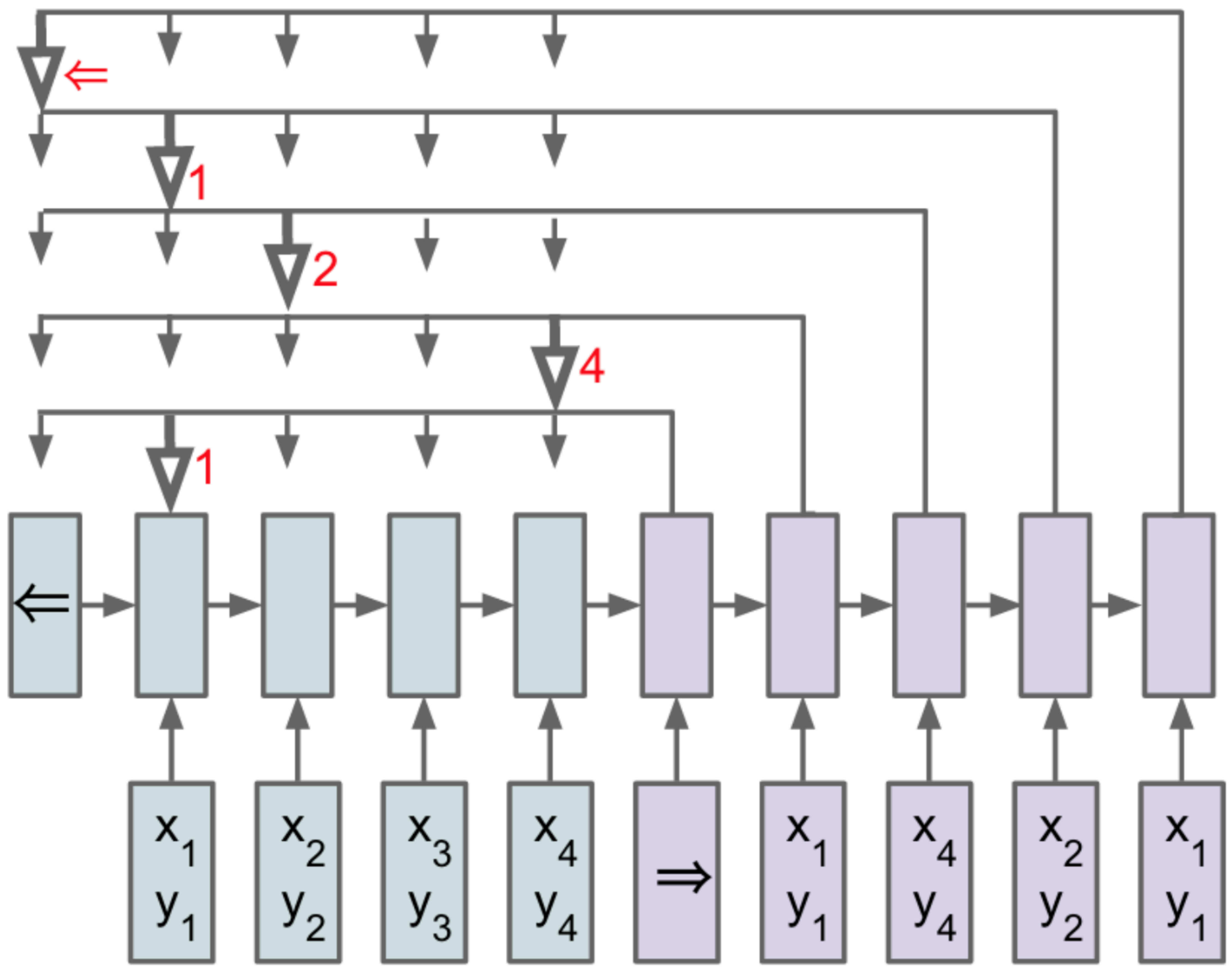
- Only point to the input, don't have any notion of vocabulary



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)

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

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

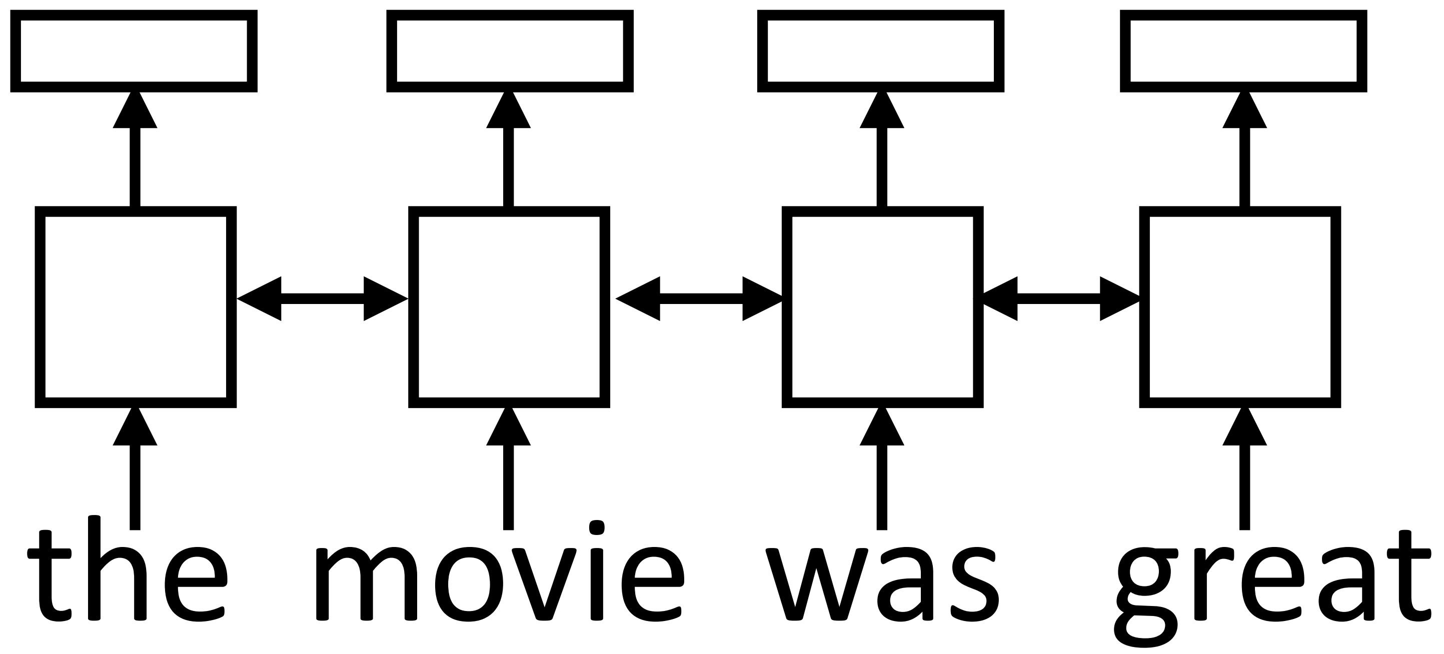
- In many settings, attention can roughly do the same things as copying

Jia and Liang (2016)

Transformers

Self-Attention

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

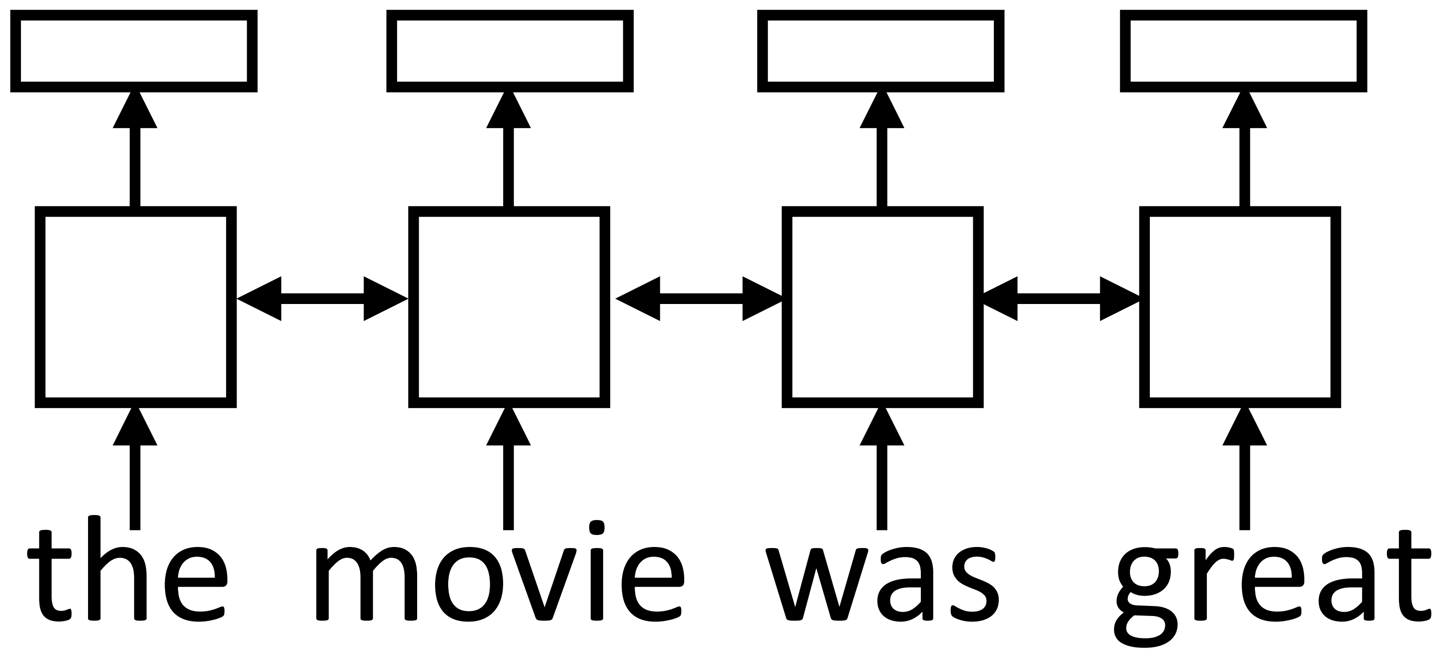


Vaswani et al. (2017)

Self-Attention

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

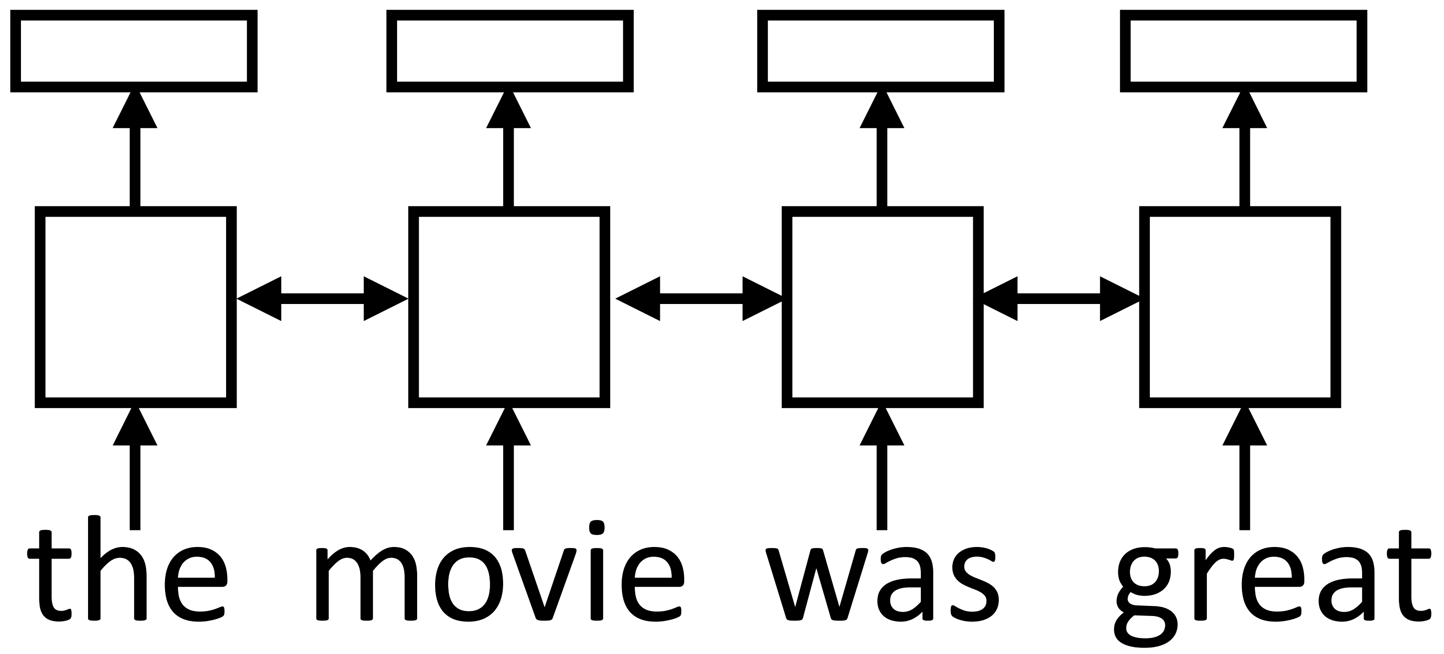
- CNNs did something similar with filters



Vaswani et al. (2017)

Self-Attention

- LSTM abstraction: maps each vector in a sentence to a new, context-aware vector
- CNNs did something similar with filters

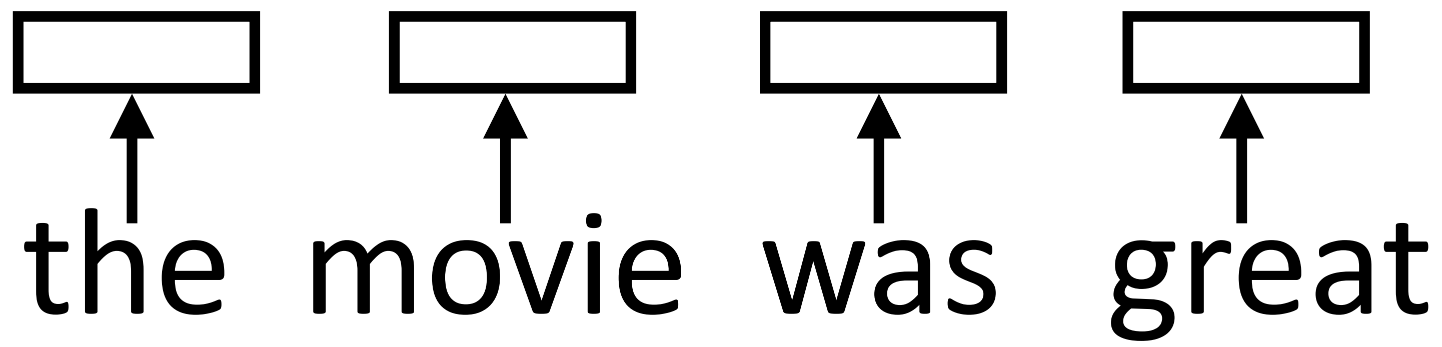


- Attention can give us a third way to do this

Vaswani et al. (2017)

Self-Attention

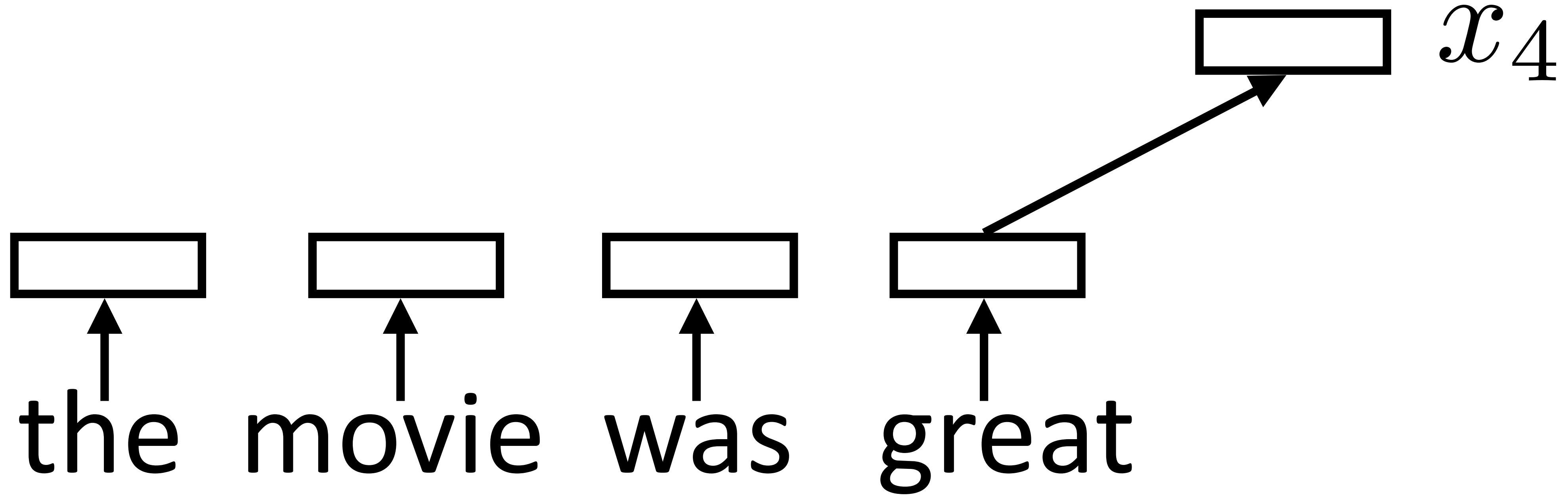
- Each word forms a "query" which then computes attention over each word



Vaswani et al. (2017)

Self-Attention

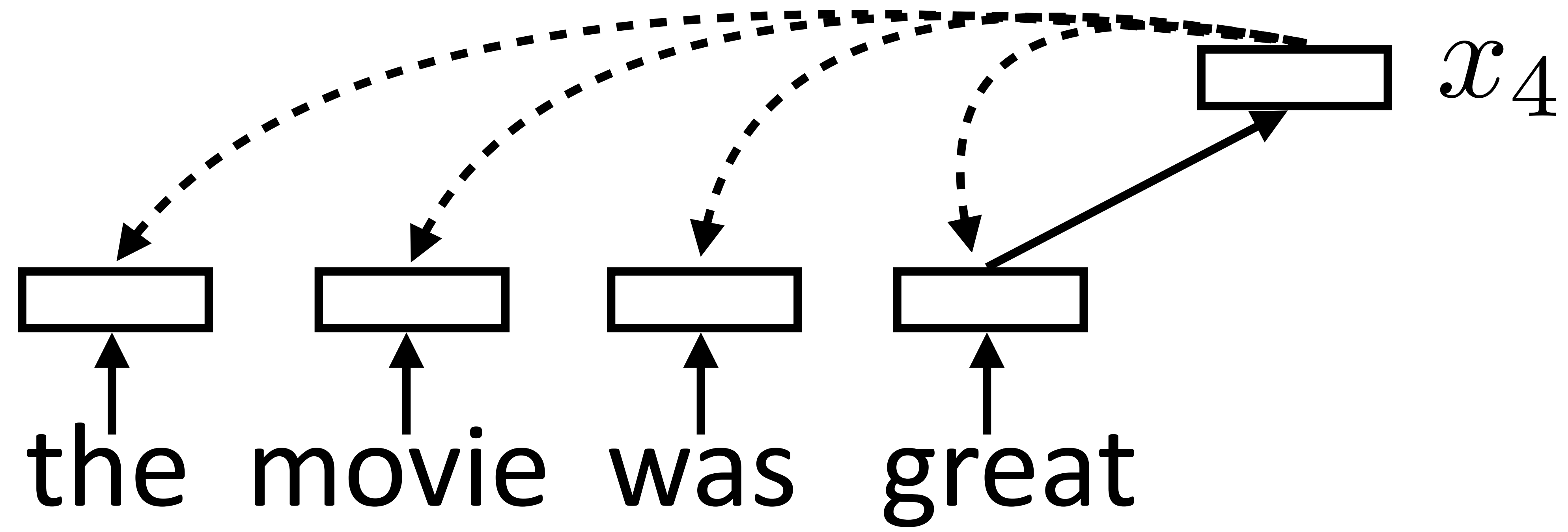
- Each word forms a “query” which then computes attention over each word



Vaswani et al. (2017)

Self-Attention

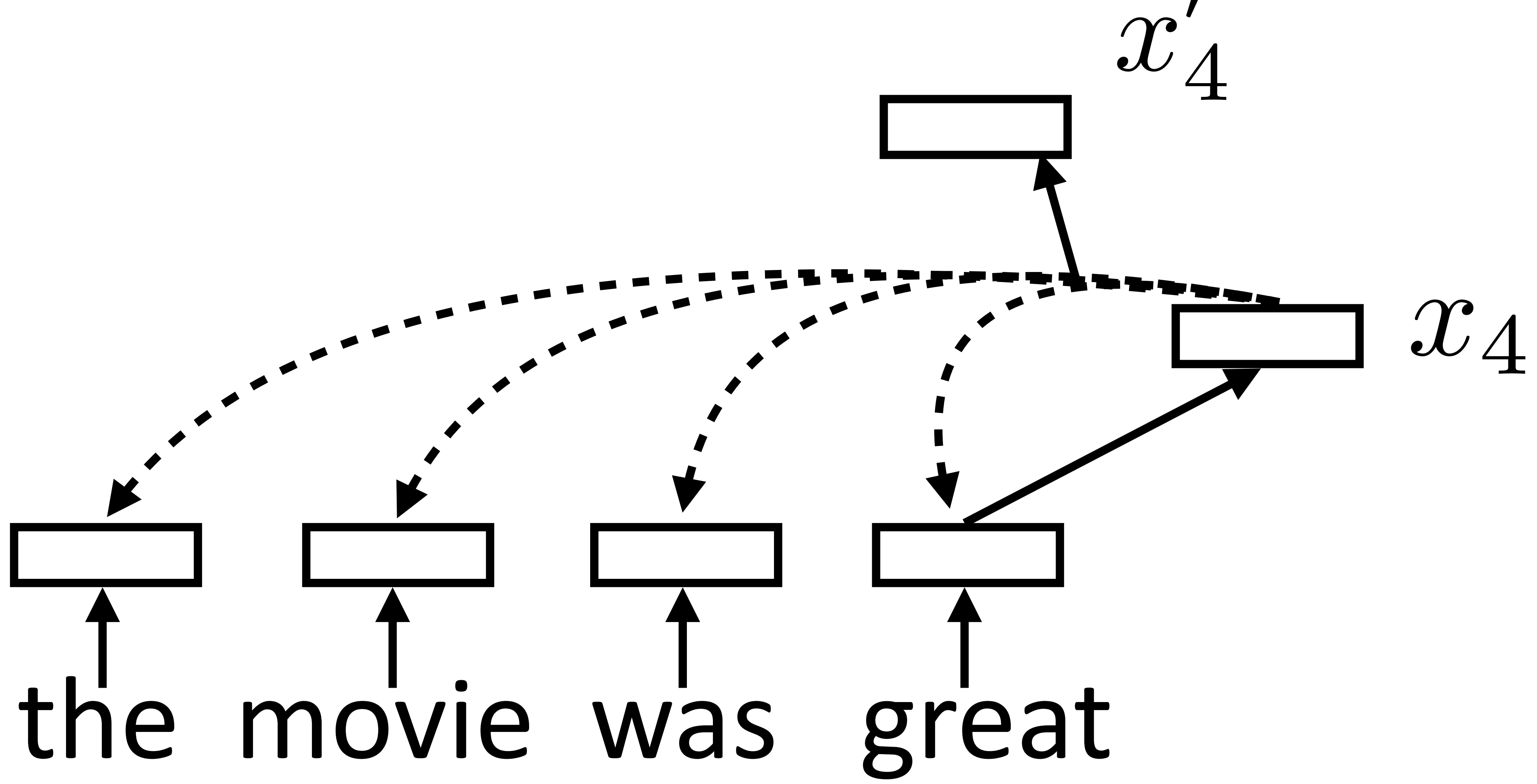
- Each word forms a "query" which then computes attention over each word



Vaswani et al. (2017)

Self-Attention

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

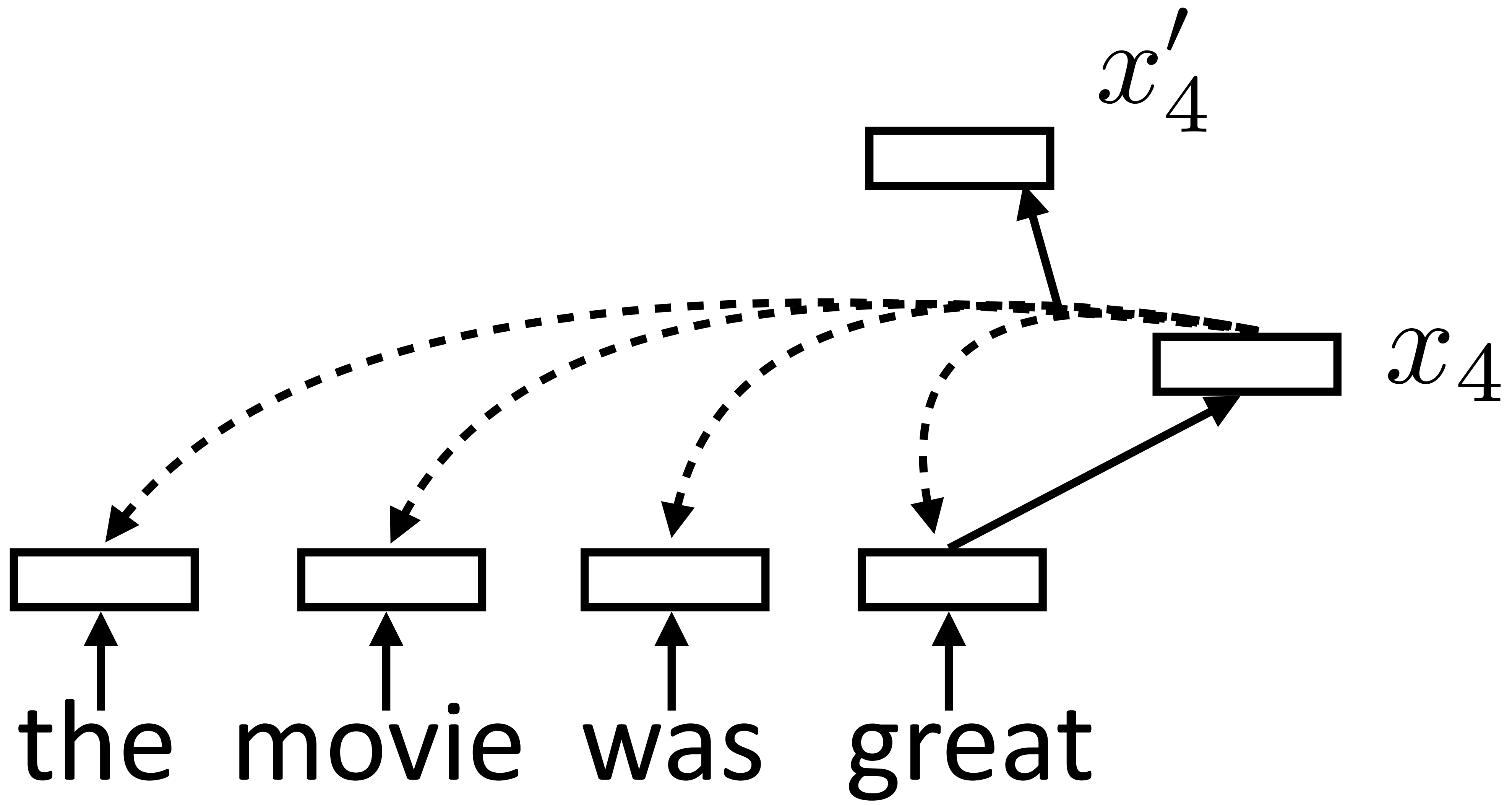


Vaswani et al. (2017)

Self-Attention

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

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



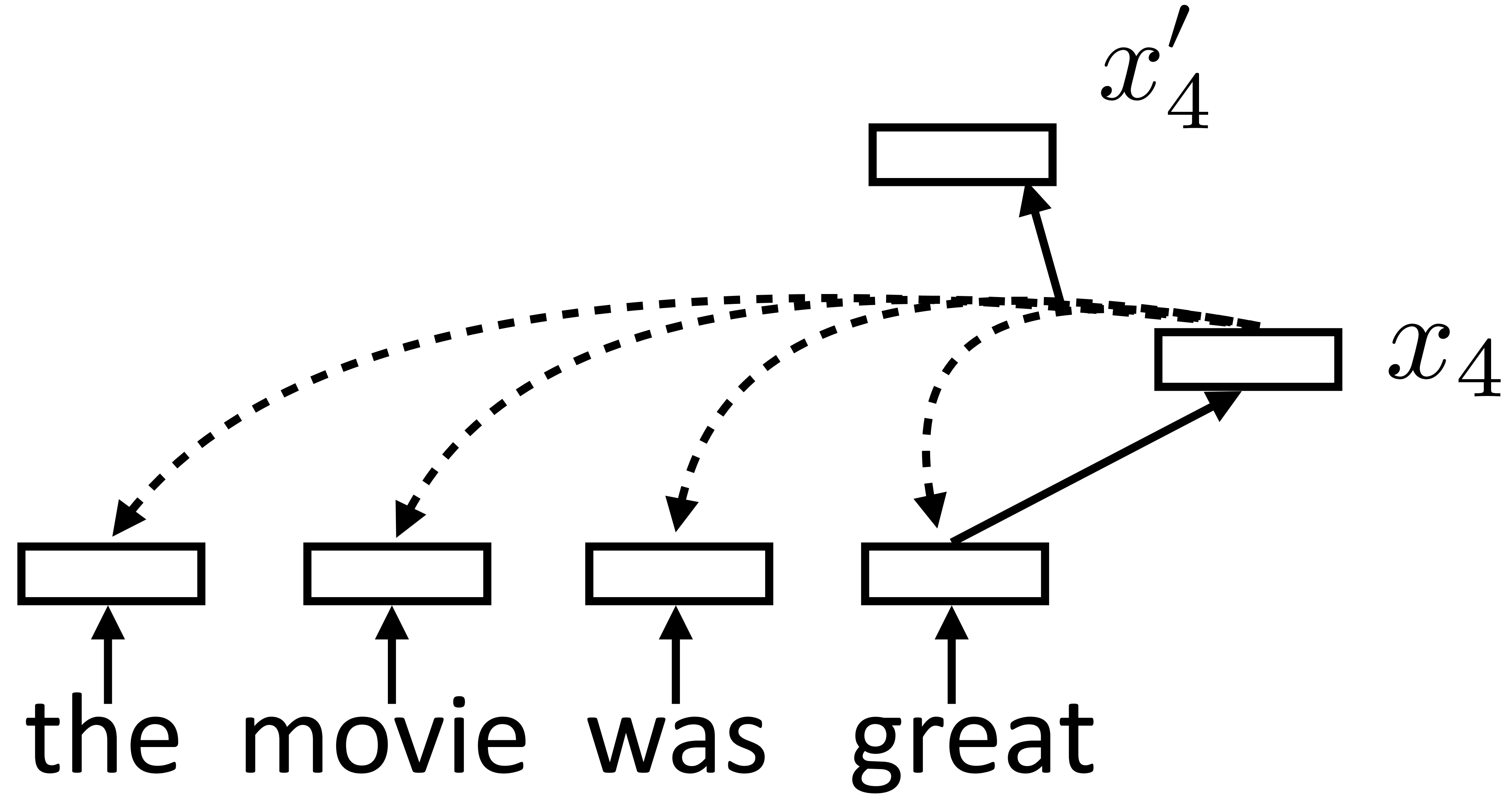
Vaswani et al. (2017)

Self-Attention

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

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

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



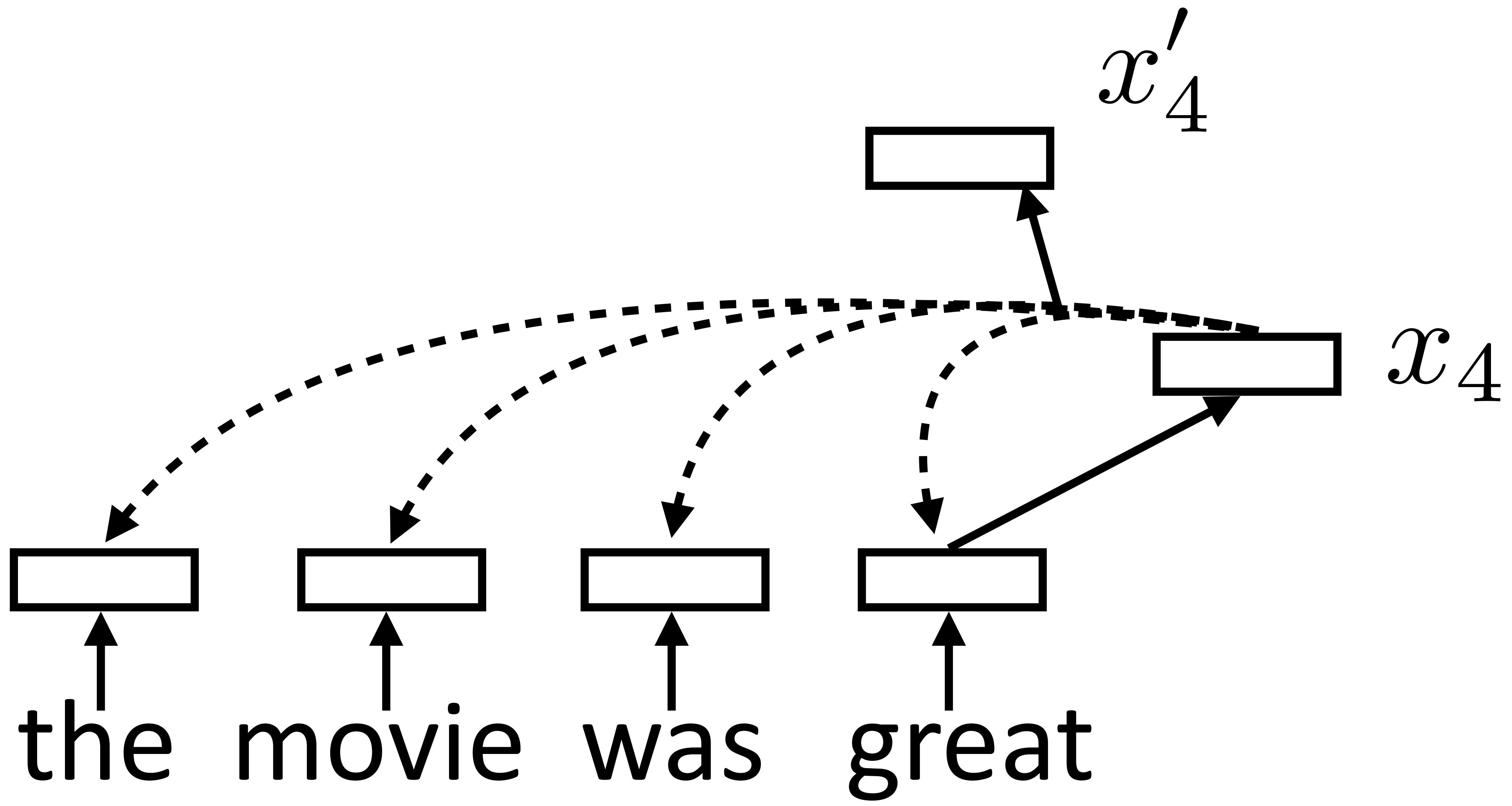
Vaswani et al. (2017)

Self-Attention

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

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

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



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

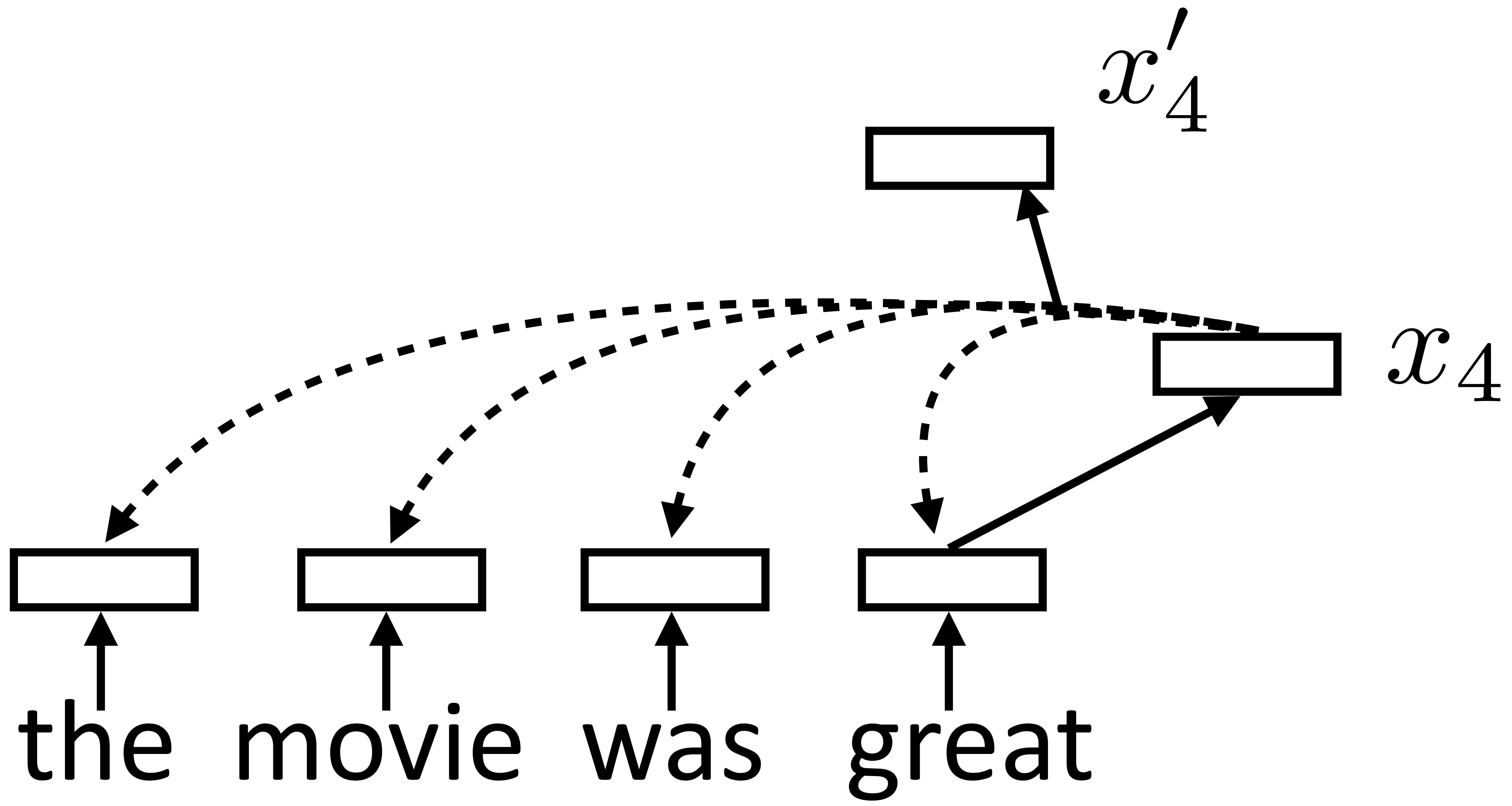
Vaswani et al. (2017)

Self-Attention

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

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

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



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

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

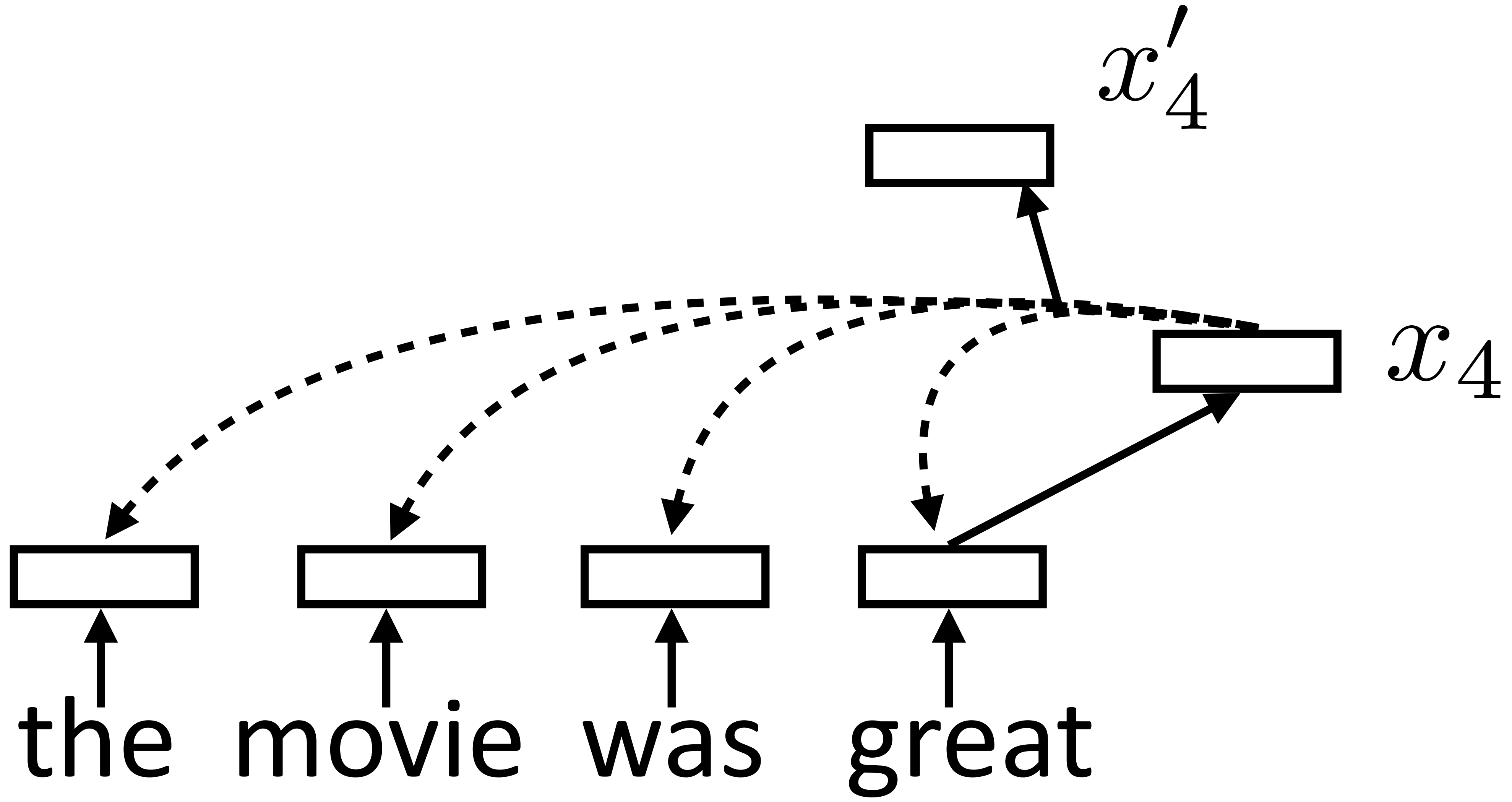
Vaswani et al. (2017)

Self-Attention

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

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

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



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

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

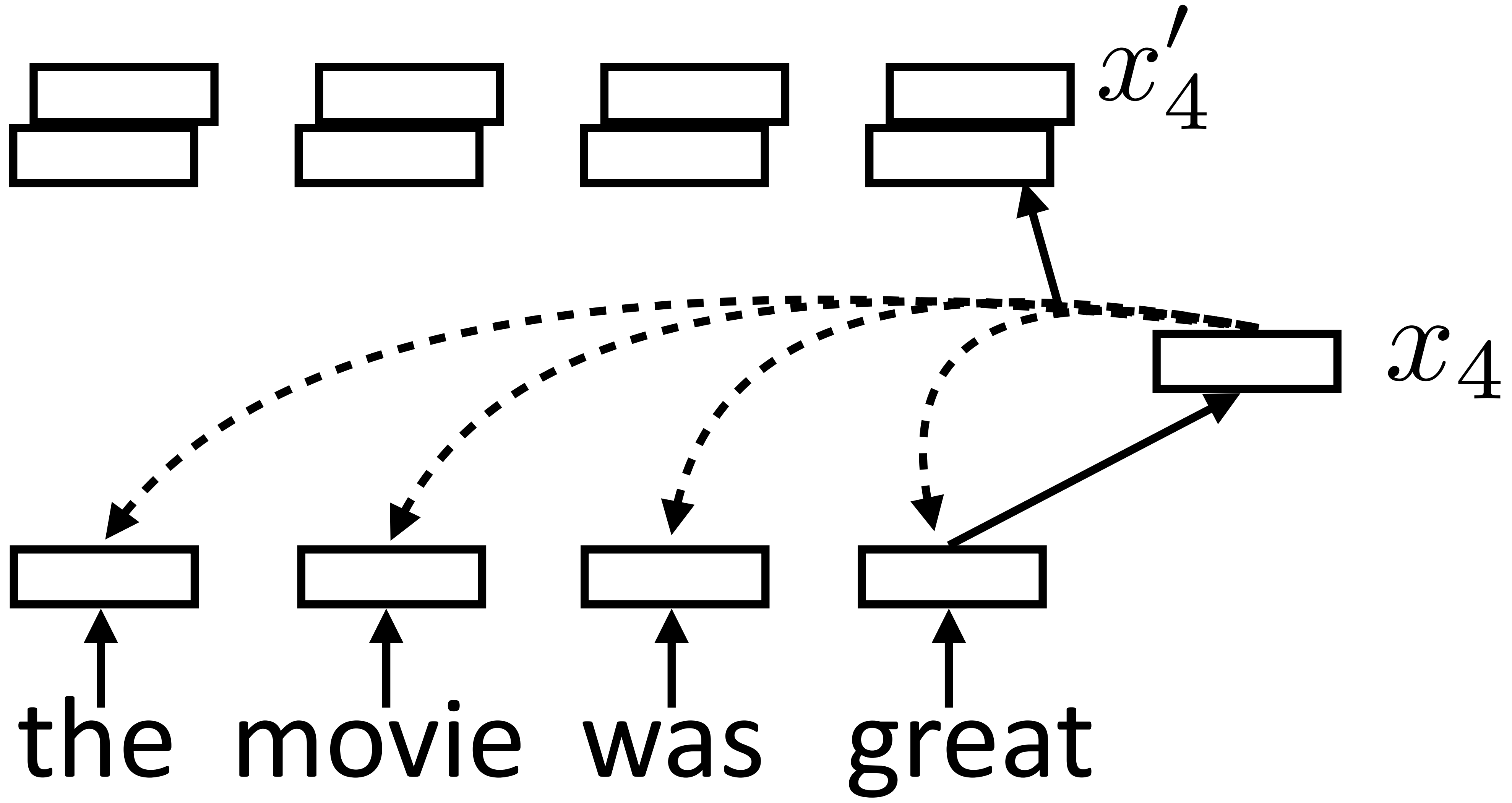
Vaswani et al. (2017)

Self-Attention

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

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

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



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

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

Vaswani et al. (2017)

Deep Transformers

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

Deep Transformers

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

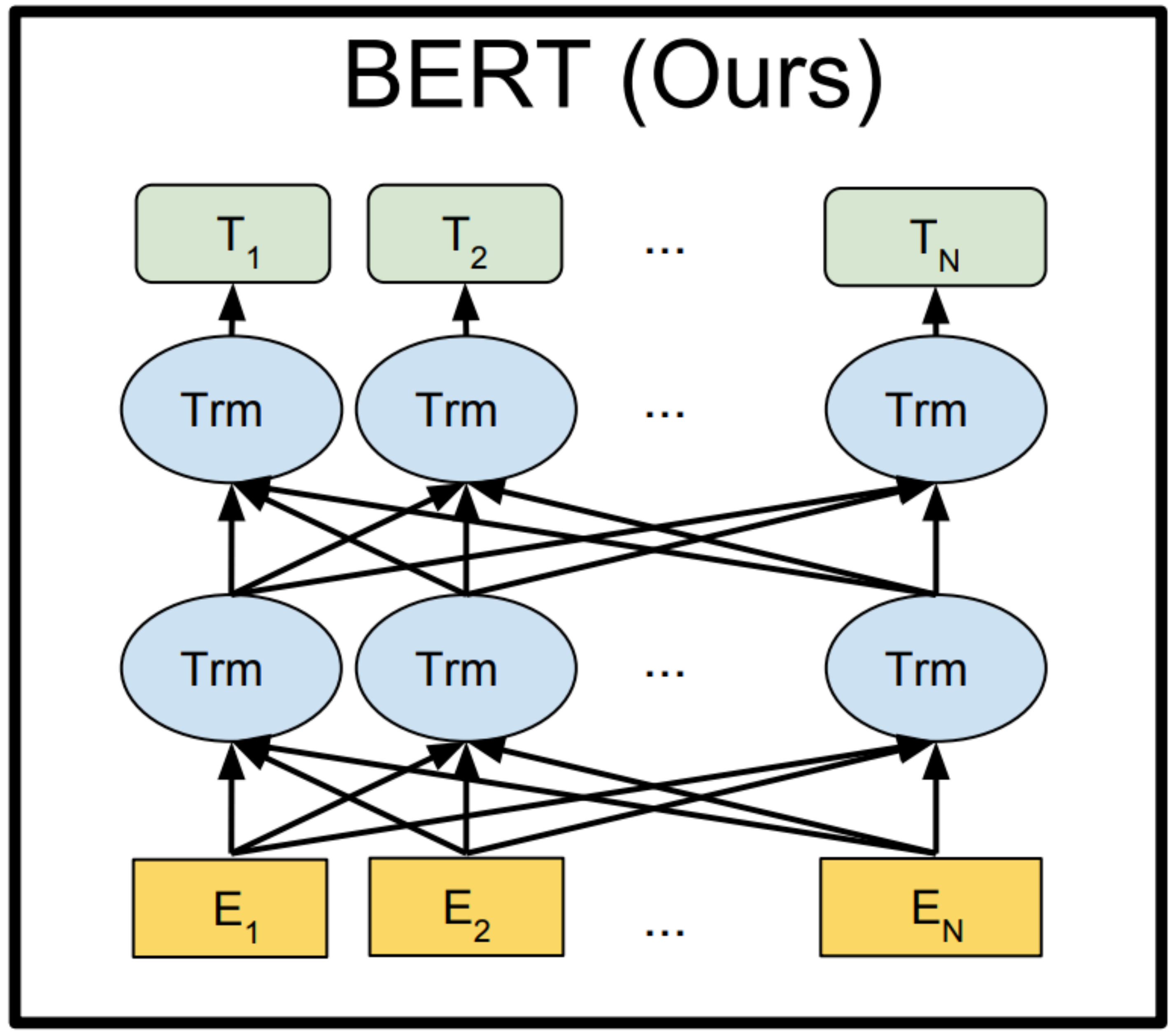
- Unsupervised: transformers work better than LSTM for unsupervised pre-training of embeddings: predict word given context words

Deep Transformers

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

- Unsupervised: transformers work better than LSTM for unsupervised pre-training of embeddings: predict word given context words

- Devlin et al. October 11, 2018
  "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"



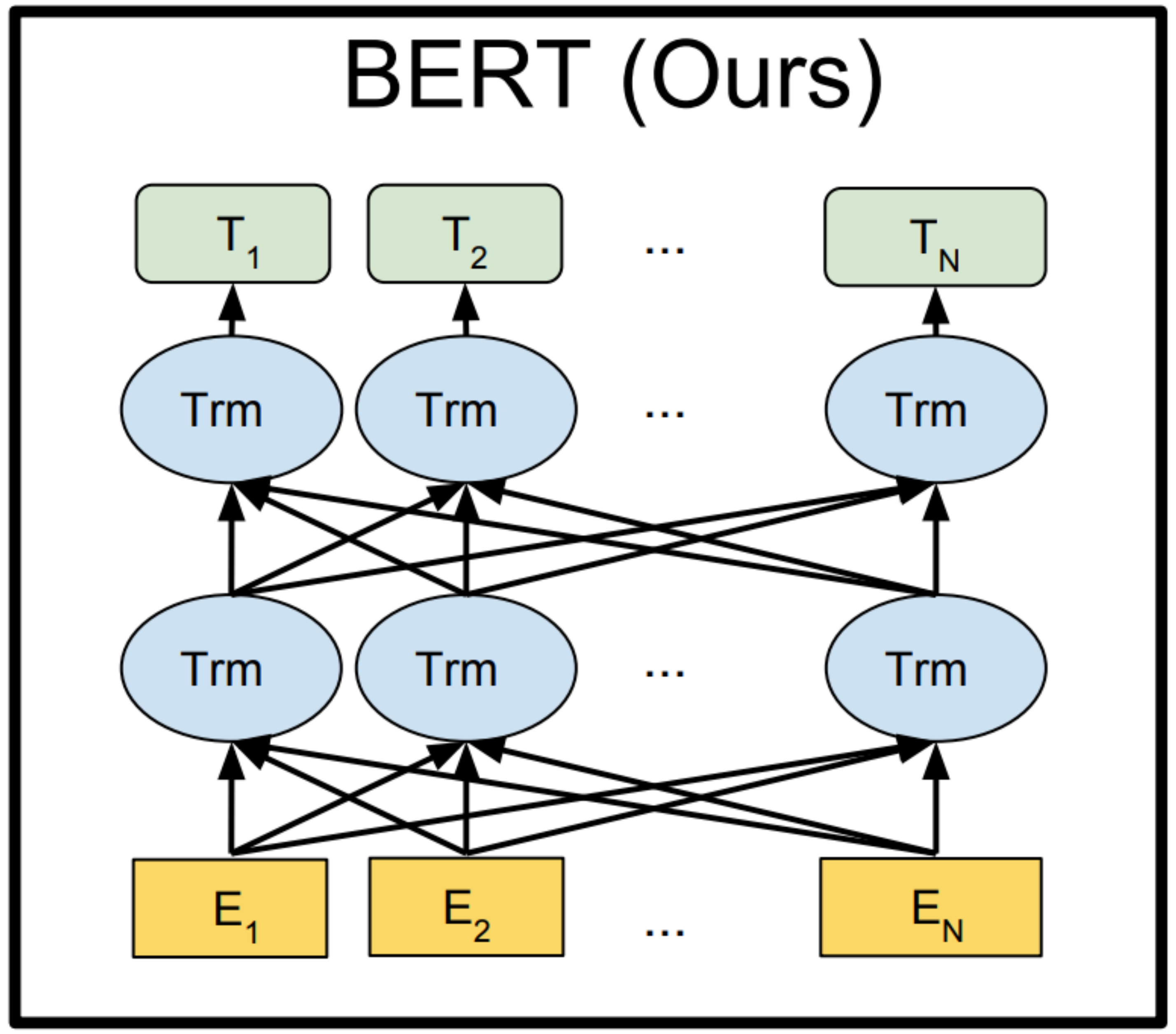
Deep Transformers

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

- Unsupervised: transformers work better than LSTM for unsupervised pre-training of embeddings: predict word given context words

- Devlin et al. October 11, 2018
  "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"

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



Takeaways

Takeaways

- Attention is very helpful for seq2seq models

Takeaways

- Attention is very helpful for seq2seq models
- Used for tasks including summarization and sentence ordering

Takeaways

- Attention is very helpful for seq2seq models
- Used for tasks including summarization and sentence ordering
- Explicitly copying input can be beneficial as well

Takeaways

- Attention is very helpful for seq2seq models
- Used for tasks including summarization and sentence ordering
- Explicitly copying input can be beneficial as well
- Transformers are strong models we'll come back to later