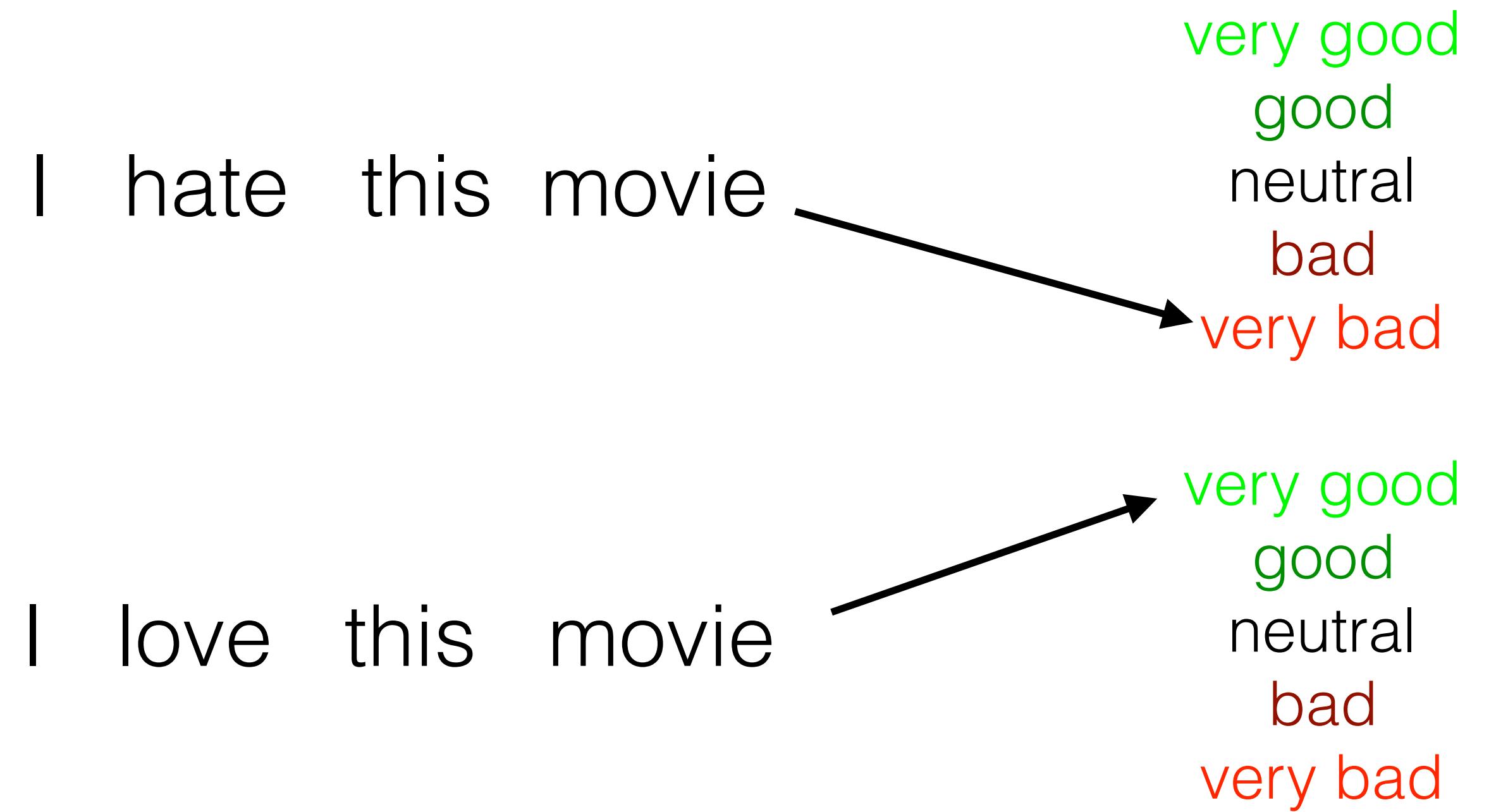


Neural Networks for Text

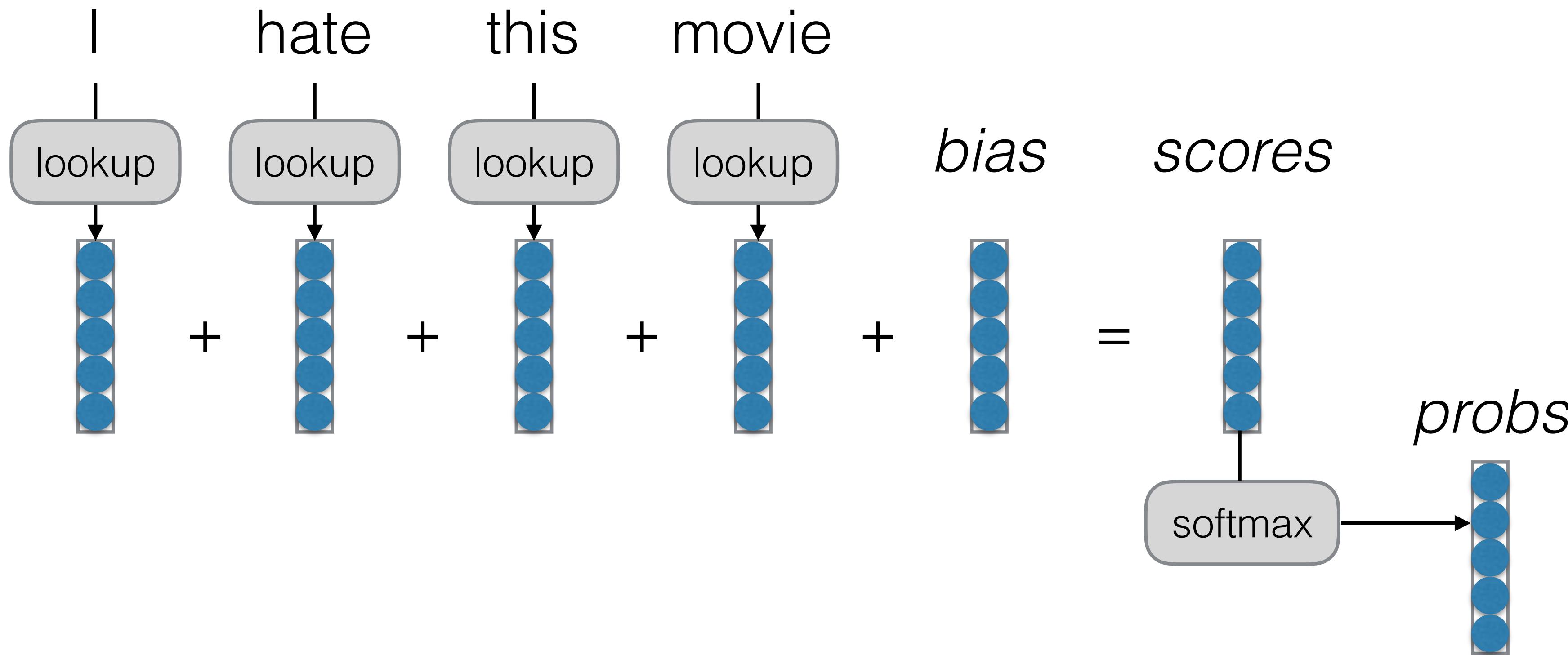
Instructor: Alan Ritter

Slides Adapted from Graham Neubig and Greg Durrett

An Example Prediction Problem: Sentence Classification



A First Try: Bag of Words (BOW)

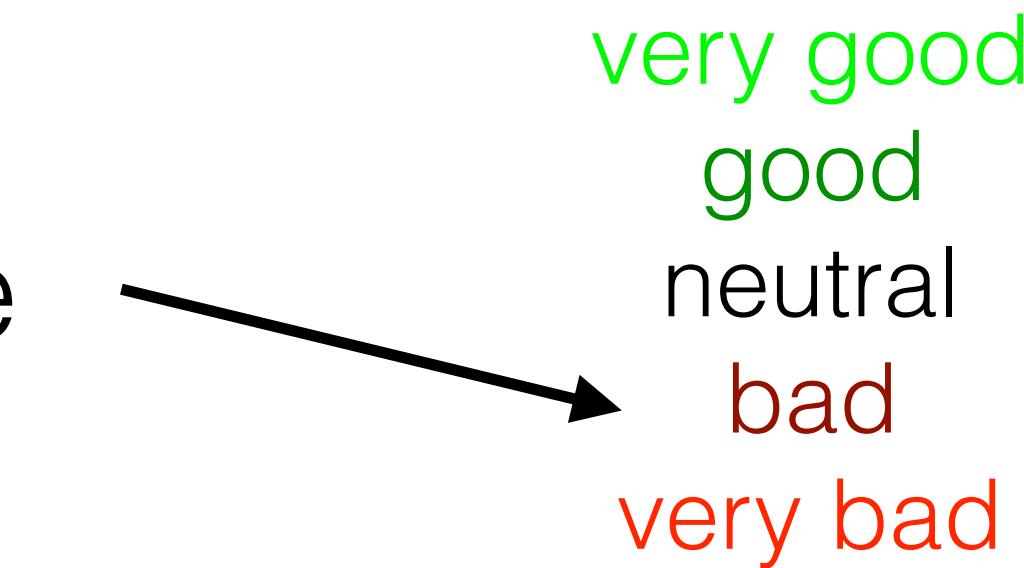


What do Our Vectors Represent?

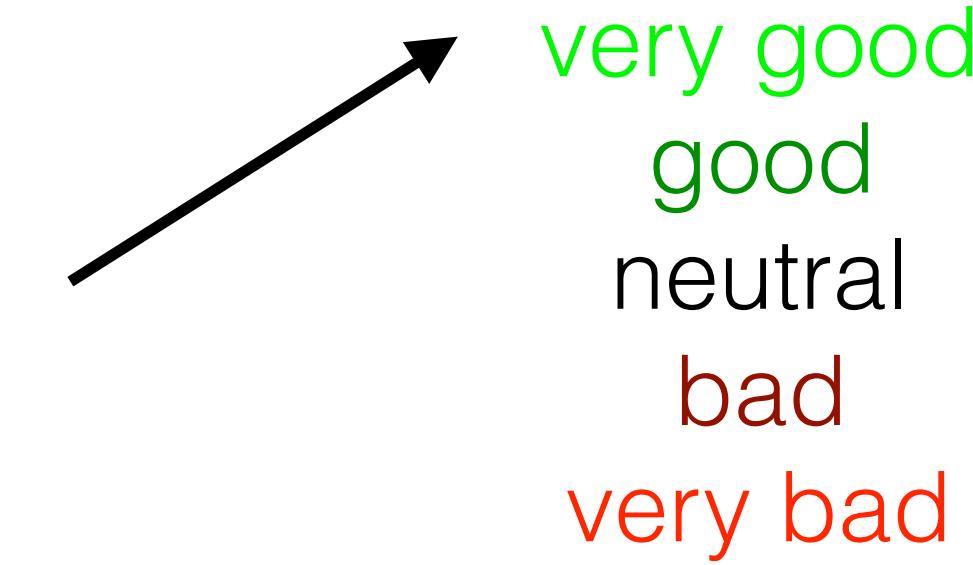
- Each word has its own 5 elements corresponding to [very good, good, neutral, bad, very bad]
- “hate” will have a high value for “very bad”, etc.

Build It, Break It

I don't love this movie



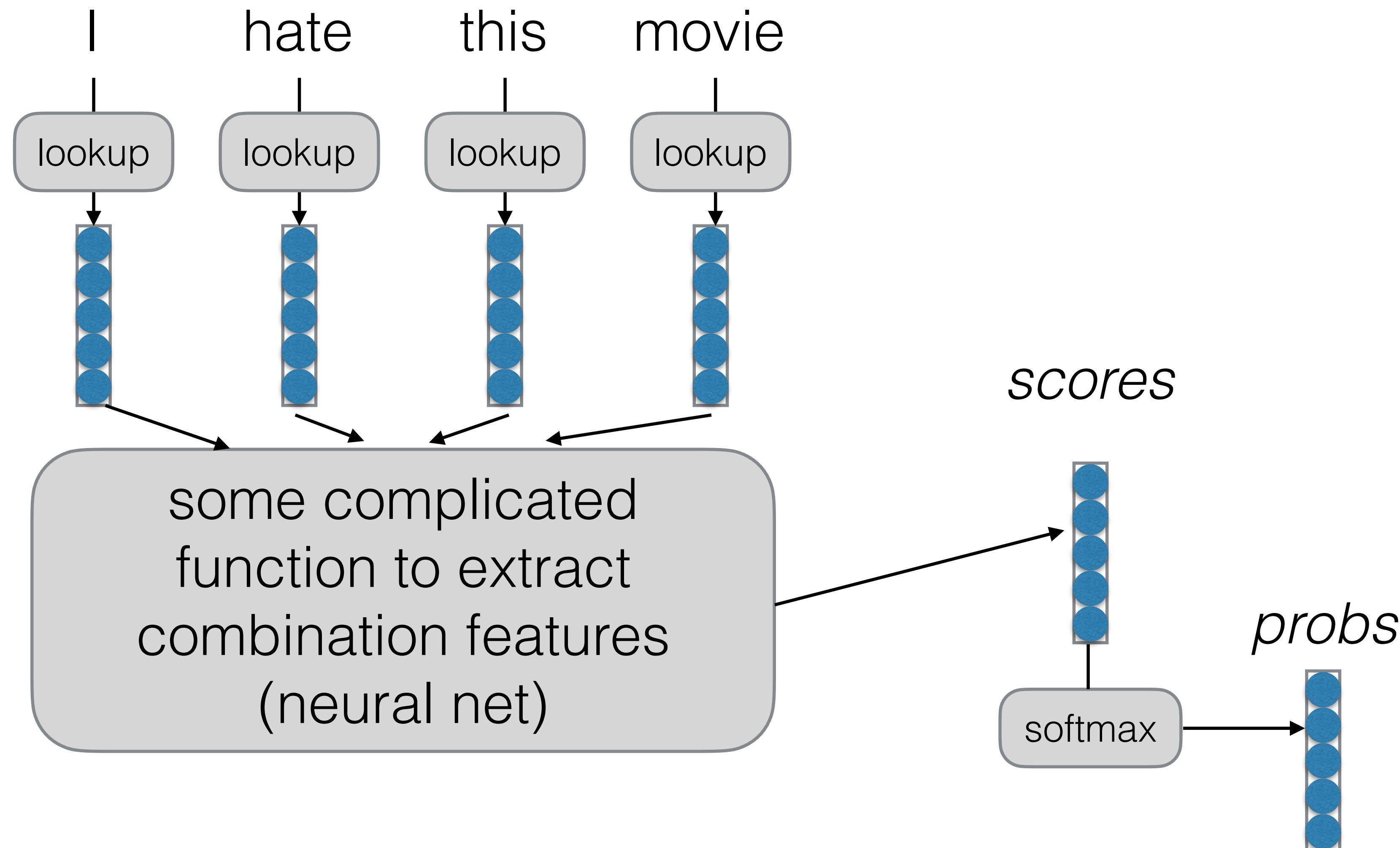
There's nothing I don't
love about this movie



Combination Features

- Does it contain “don’t” and “love”?
- Does it contain “don’t”, “i”, “love”, and “nothing”?

Basic Idea of Neural Networks (for NLP Prediction Tasks)



1.10.0 ▼

 Search Docs

Notes [+]

Language Bindings [+]

Python API [-]

torch

● torch.nn

torch.nn.functional

torch.Tensor

Tensor Attributes

Tensor Views

torch.autograd

torch.cuda

Docs > torch.nn > Embedding

[>]

EMBEDDING

Embedding

CLASS `torch.nn.Embedding(num_embeddings, embedding_dim, padding_idx=None, max_norm=None, norm_type=2.0, scale_grad_by_freq=False, sparse=False, _weight=None, device=None, dtype=None)` [\[SOURCE\]](#)

A simple lookup table that stores embeddings of a fixed dictionary and size.

This module is often used to store word embeddings and retrieve them using indices. The input to the module is a list of indices, and the output is the corresponding word embeddings.

Parameters

- **num_embeddings** (*int*) – size of the dictionary of embeddings
- **embedding_dim** (*int*) – the size of each embedding vector
- **padding_idx** (*int, optional*) – If specified, the entries at `padding_idx` do not contribute to the

1.10.0 ▼

Docs > torch.nn > Embedding



Search Docs

Notes [+]

Language Bindings [+]

Python API [-]

torch

● torch.nn

torch.nn.functional

torch.Tensor

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Tensor Views

torch.autograd

torch.cuda

EMBEDDING

Embedding

```
CLASS torch.nn.Embedding(num_embeddings, embedding_dim, padding_idx=None,  
                         max_norm=None, norm_type=2.0, scale_grad_by_freq=False, sparse=False,  
                         _weight=None, device=None, dtype=None) [SOURCE]
```

A simple lookup table that stores embeddings of a fixed dictionary and size.

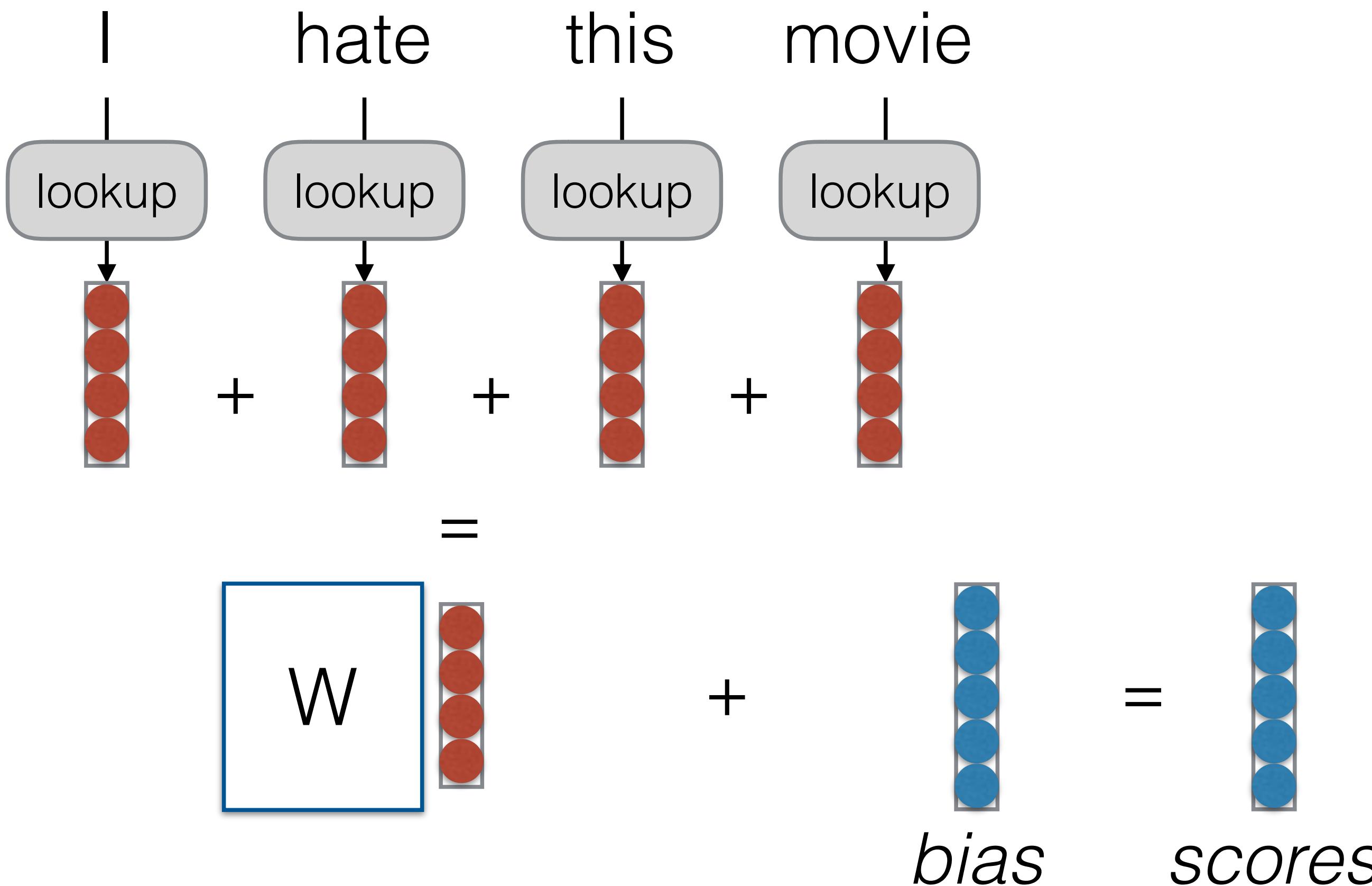
This module is often used when you have a fixed set of items, like an vocabulary, and you want to convert between the list of indices, and the one-hot vectors.

Parameters

- **num_embeddings**
- **embedding_dim**
- **padding_idx**

```
>>> # an Embedding module containing 10 tensors of size 3  
>>> embedding = nn.Embedding(10, 3)  
>>> # a batch of 2 samples of 4 indices each  
>>> input = torch.LongTensor([[1,2,4,5],[4,3,2,9]])  
>>> embedding(input)  
tensor([[[ -0.0251, -1.6902,  0.7172],  
        [-0.6431,  0.0748,  0.6969],  
        [ 1.4970,  1.3448, -0.9685],  
        [-0.3677, -2.7265, -0.1685]],  
  
       [[ 1.4970,  1.3448, -0.9685],  
        [ 0.4362, -0.4004,  0.9400],  
        [-0.6431,  0.0748,  0.6969],  
        [ 0.9124, -2.3616,  1.1151]]])
```

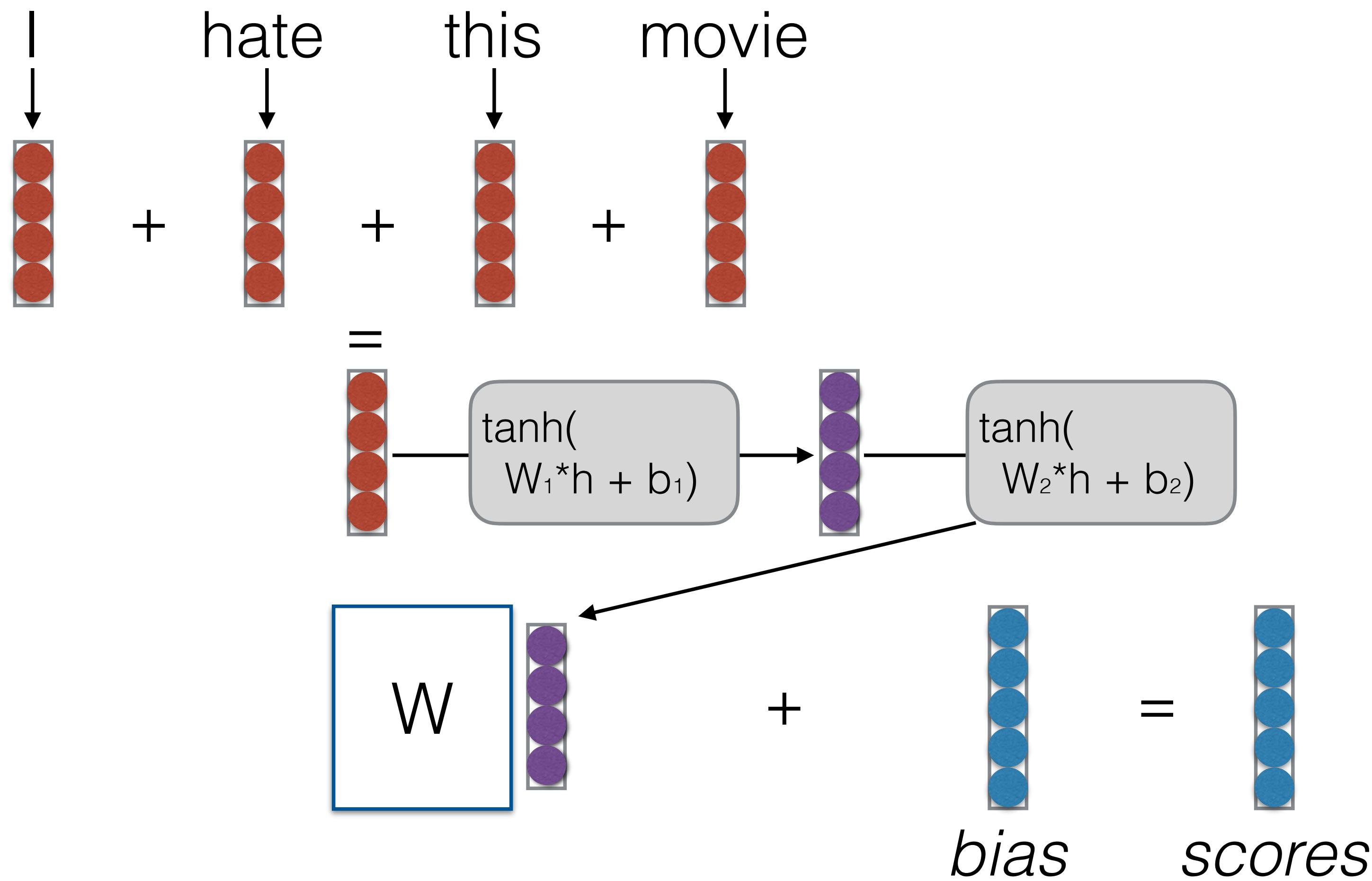
Continuous Bag of Words (CBOW)



What do Our Vectors Represent?

- Each vector has “features” (e.g. is this an animate object? is this a positive word, etc.)
- We sum these features, then use these to make predictions
- Still no combination features: only the expressive power of a linear model, but dimension reduced

Deep CBOW

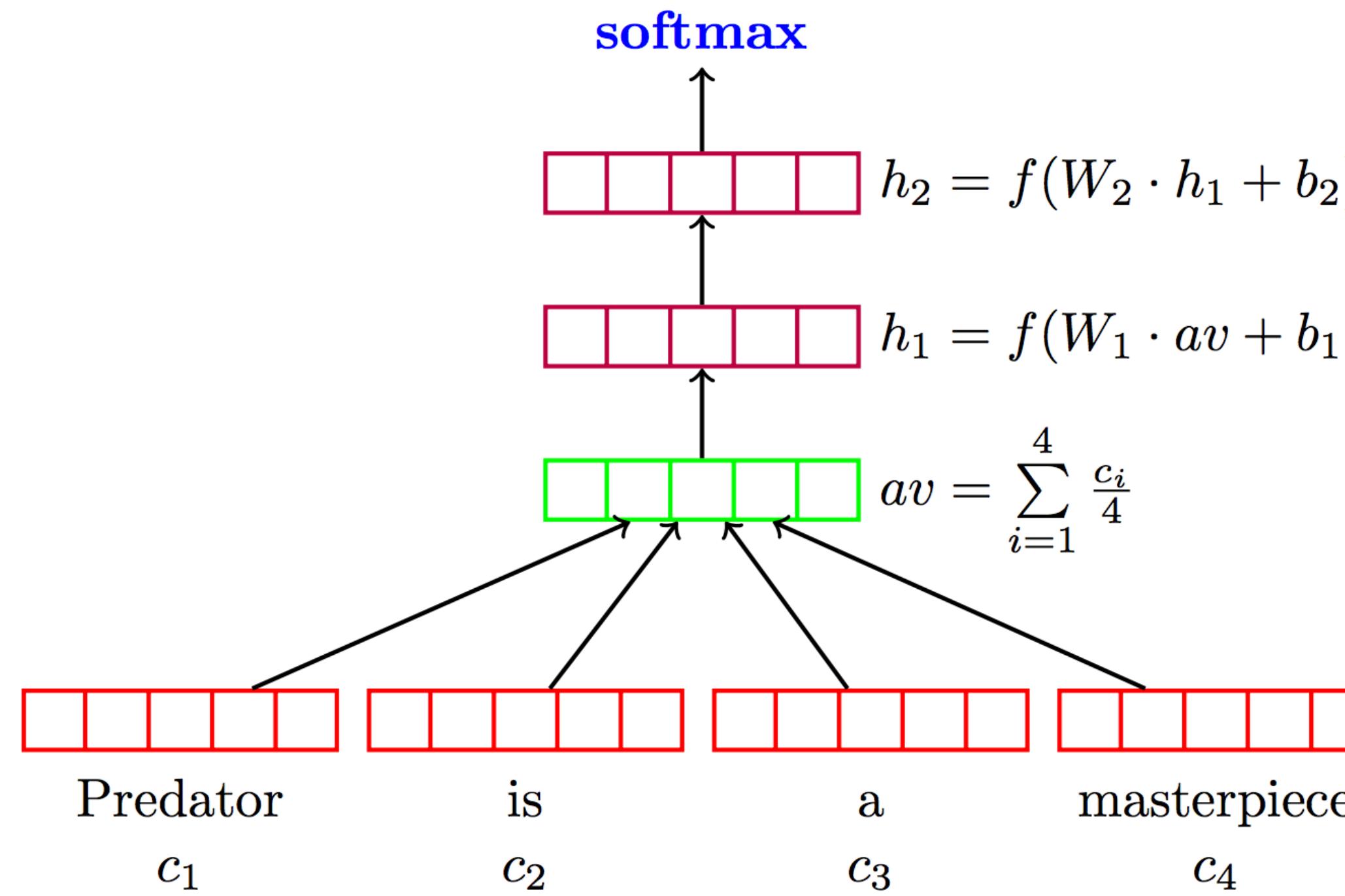


What do Our Vectors Represent?

- Now things are more interesting!
- We can learn feature combinations (a node in the second layer might be “feature 1 AND feature 5 are active”)
- e.g. capture things such as “not” AND “hate”

Sentiment Analysis

Deep Averaging Networks: feedforward neural network
on average of word embeddings from input



Iyyer et al. (2015)

Sentiment Analysis

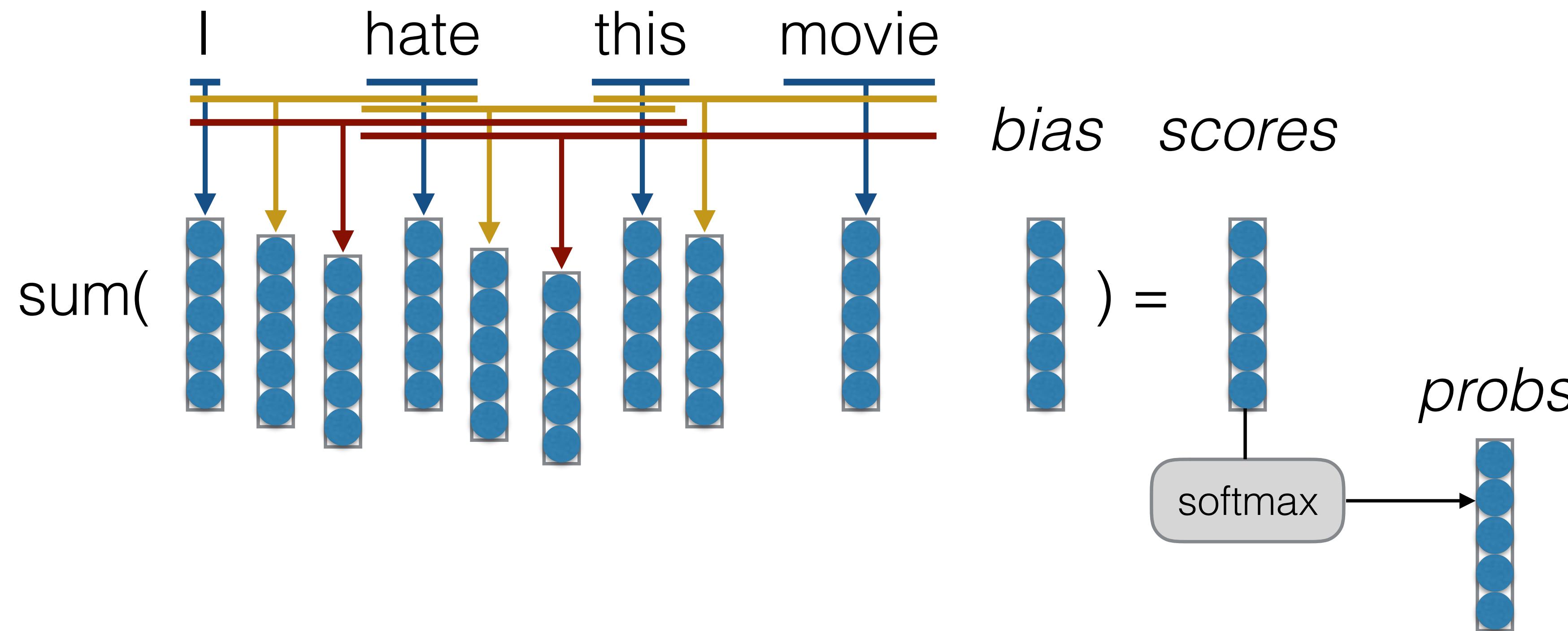
	Model	RT	SST fine	SST bin	IMDB	Time (s)
DAN-ROOT	—	46.9	85.7	—	—	31
DAN-RAND	77.3	45.4	83.2	88.8	136	
DAN	80.3	47.7	86.3	89.4	136	
Bag-of-words	NBOW-RAND	76.2	42.3	81.4	88.9	91
	NBOW	79.0	43.6	83.6	89.0	91
	BiNB	—	41.9	83.1	—	—
	NBSVM-bi	79.4	—	—	91.2	—
Tree RNNs / CNNs / LSTMs	RecNN*	77.7	43.2	82.4	—	—
	RecNTN*	—	45.7	85.4	—	—
	DRecNN	—	49.8	86.6	—	431
	TreeLSTM	—	50.6	86.9	—	—
	DCNN*	—	48.5	86.9	89.4	—
	PVEC*	—	48.7	87.8	92.6	—
	CNN-MC	81.1	47.4	88.1	—	2,452
	WRRBM*	—	—	—	89.2	—

Iyyer et al. (2015)

Wang and
Manning
(2012)

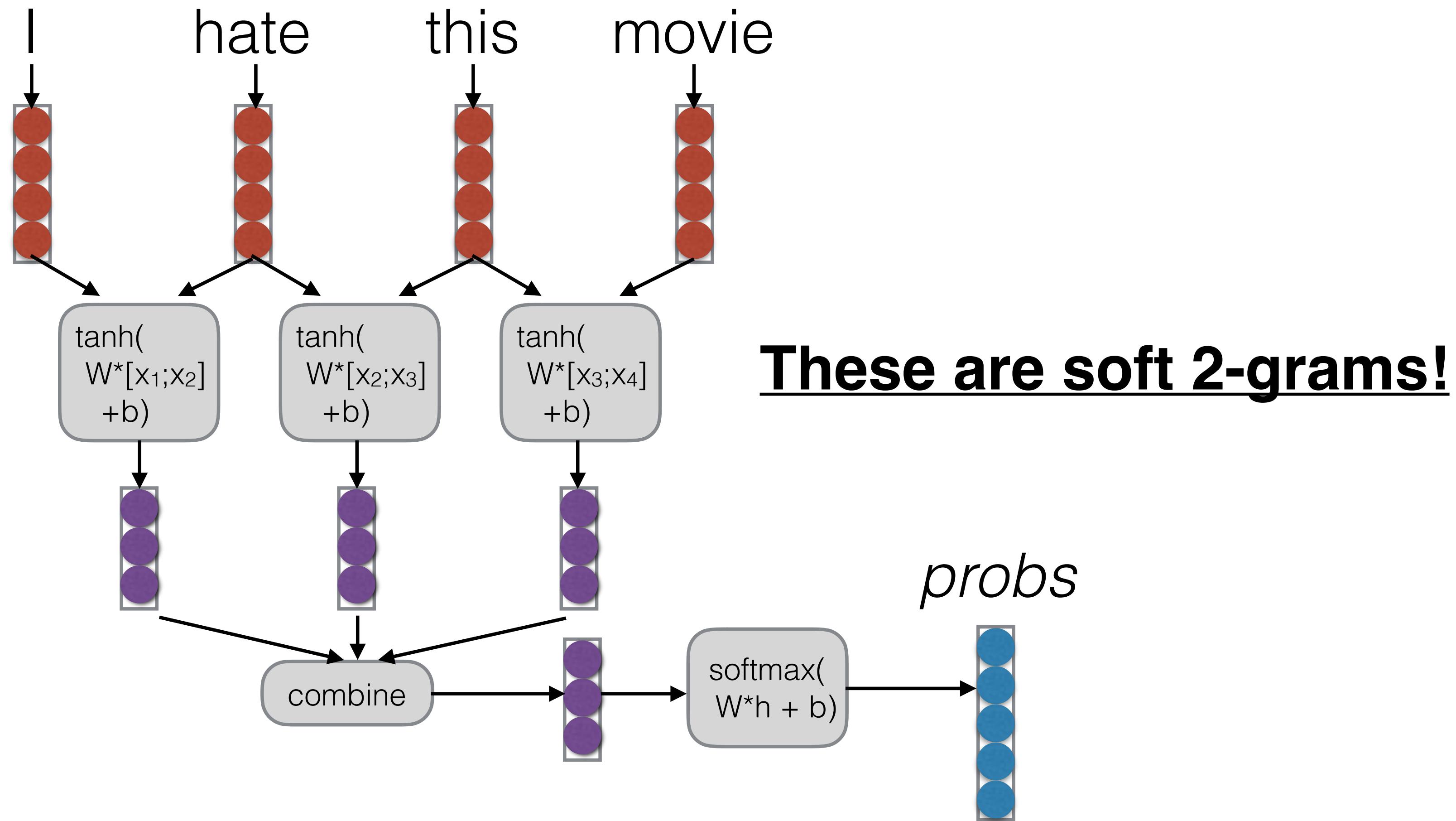
Kim (2014)

Bag of n-grams



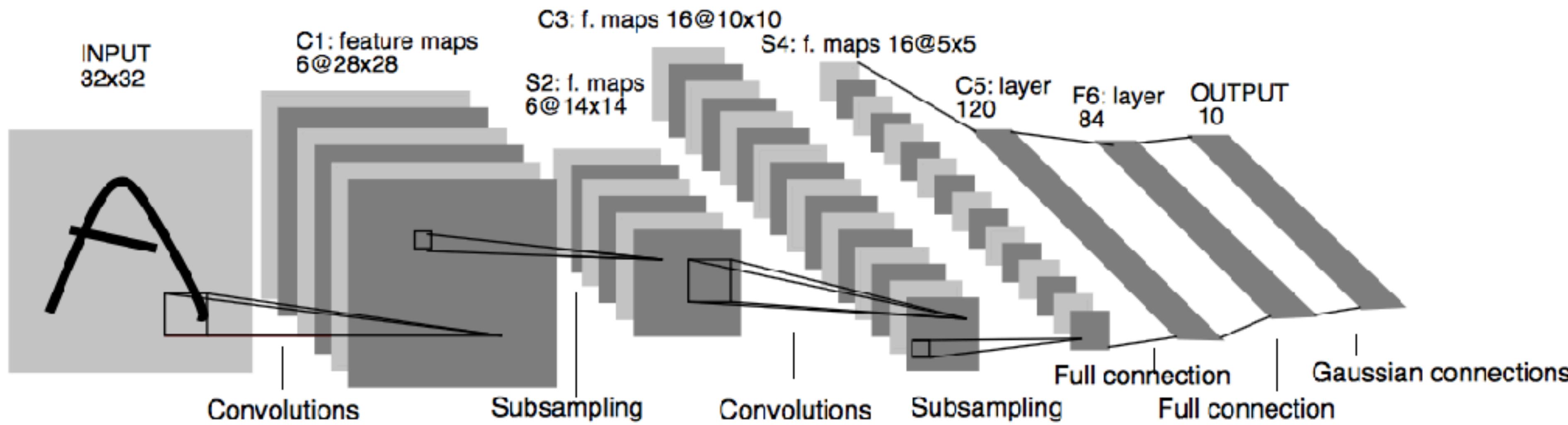
Time Delay Neural Networks

(Waibel et al. 1989)



Convolutional Networks

(LeCun et al. 1997)



Parameter extraction performs a 2D sweep, not 1D

1 <small>x1</small>	1 <small>x0</small>	1 <small>x1</small>	0	0
0 <small>x0</small>	1 <small>x1</small>	1 <small>x0</small>	1	0
0 <small>x1</small>	0 <small>x0</small>	1 <small>x1</small>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

1 <small>x1</small>	1 <small>x0</small>	1 <small>x1</small>	0	0
0 <small>x0</small>	1 <small>x1</small>	1 <small>x0</small>	1	0
0 <small>x1</small>	0 <small>x0</small>	1 <small>x1</small>	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

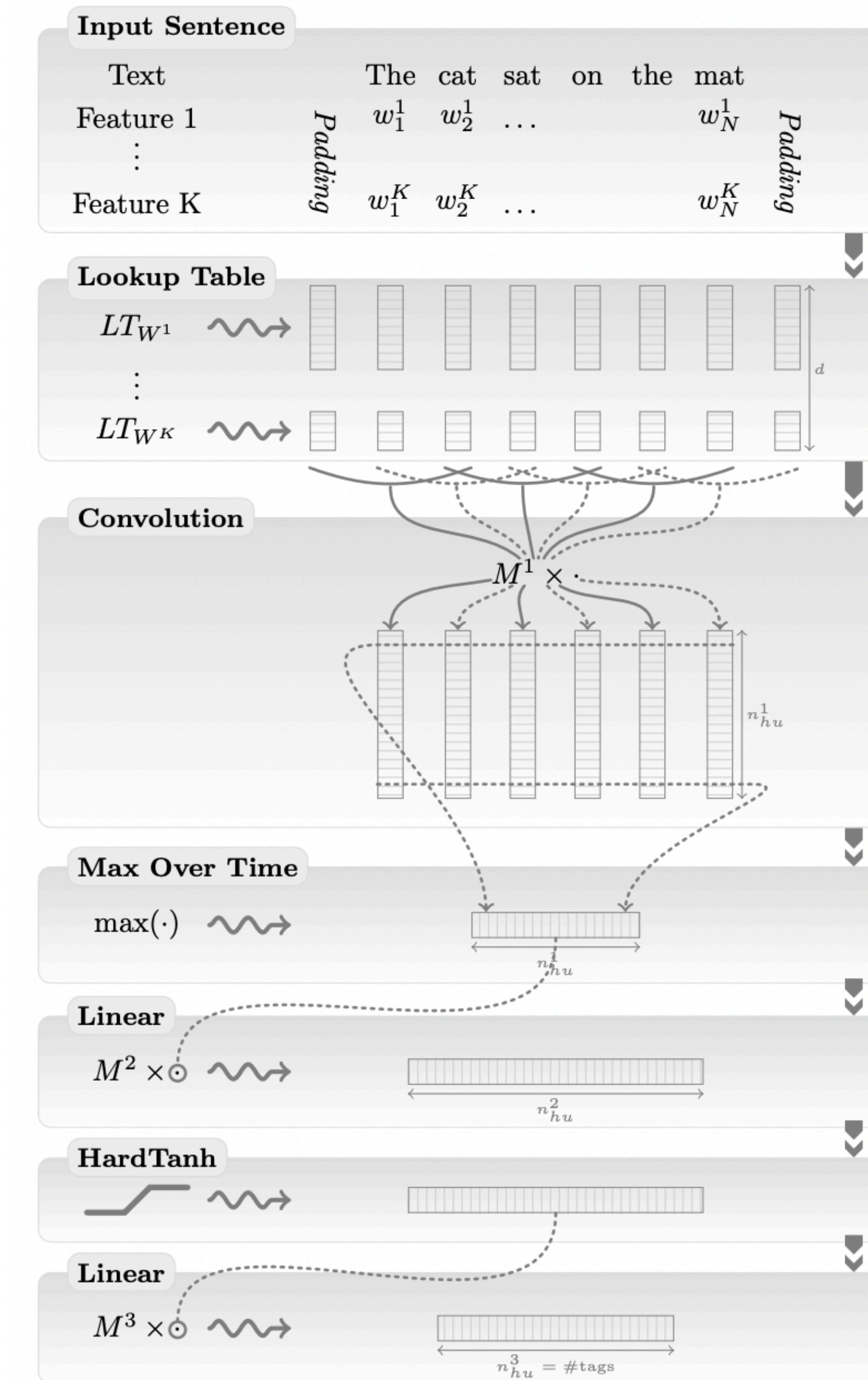
CNNs for Text

(Collobert and Weston 2011)

- 1D convolution \approx Time Delay Neural Network
 - But often uses terminology/functions borrowed from image processing
- Two main paradigms:
 - **Context window modeling:** For tagging, etc. get the surrounding context before tagging
 - **Sentence modeling:** Do convolution to extract n-grams, pooling to combine over whole sentence

CNNs for Sentence Modeling

(Collobert and Weston 2011)

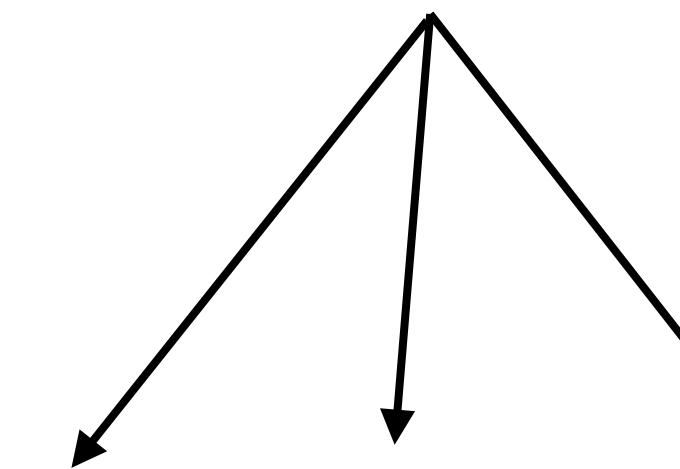


Sentence Classification

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	88.1	93.2	92.2	85.0	89.4
NBSVM (Wang and Manning, 2012)	79.4	-	-	93.2	-	81.8	86.3

Sentence Classification

movie review
sentiment



Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	88.1	93.2	92.2	85.0	89.4
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Sentence Classification

movie review
sentiment

subjectivity/objectivity
detection

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	88.1	93.2	92.2	85.0	89.4
NBSVM (Wang and Manning, 2012)	79.4	-	-	93.2	-	81.8	86.3

Sentence Classification

The diagram illustrates the application of various sentence classification models across different NLP tasks. Three arrows point from descriptive text labels to specific columns in the table:

- An arrow points from the text "movie review sentiment" to the second column (SST-1).
- An arrow points from the text "subjectivity/objectivity detection" to the fourth column (Subj).
- An arrow points from the text "question type classification" to the eighth column (MPQA).

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	88.1	93.2	92.2	85.0	89.4
NBSVM (Wang and Manning, 2012)	79.4	-	-	93.2	-	81.8	86.3

Sentence Classification

The diagram illustrates the application of the CNN-multichannel model across various NLP tasks. Arrows point from the task names to the corresponding columns in the table:

- An arrow points from "movie review sentiment" to the SST-1 column.
- An arrow points from "subjectivity/objectivity detection" to the Subj column.
- An arrow points from "product reviews" to the CR column.
- An arrow points from "question type classification" to the MPQA column.

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	88.1	93.2	92.2	85.0	89.4
NBSVM (Wang and Manning, 2012)	79.4	-	-	93.2	-	81.8	86.3

Sentence Classification

The diagram illustrates the application of sentence classification models across various domains. Arrows point from the text descriptions to the corresponding columns in the table.

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-multichannel	81.1	47.4	88.1	93.2	92.2	85.0	89.4
NBSVM (Wang and Manning, 2012)	79.4	-	-	93.2	-	81.8	86.3

movie review sentiment → SST-1, SST-2
subjectivity/objectivity detection → Subj
product reviews → CR
question type classification → TREC

- ▶ Also effective at document-level text classification

RNN Basics

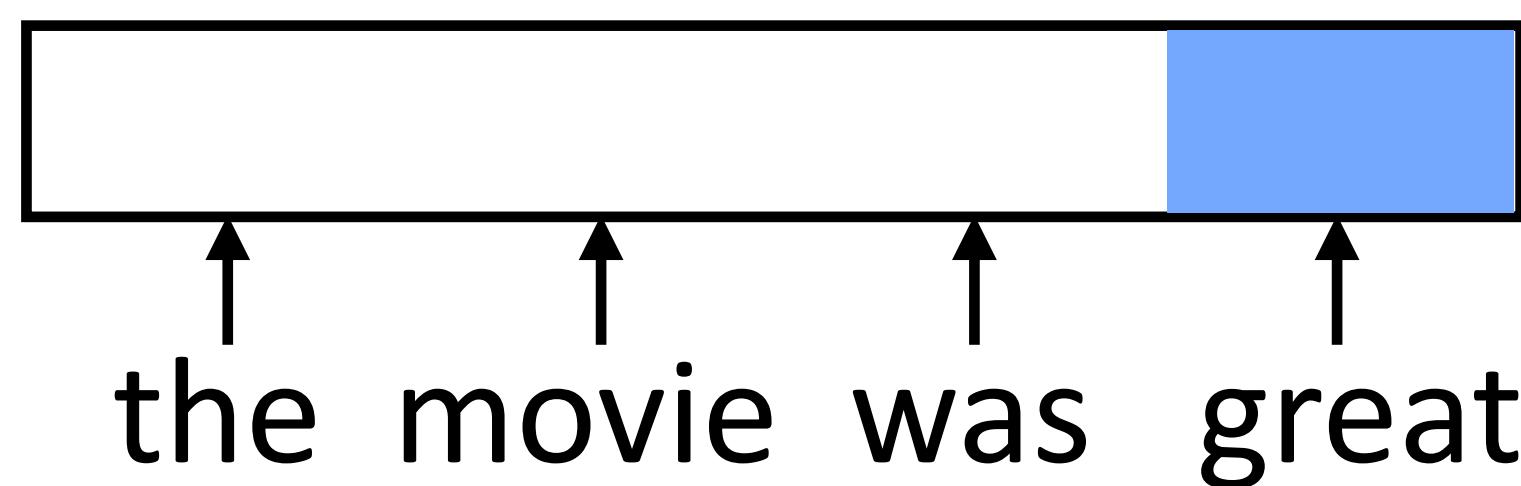
RNN Motivation

- ▶ Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics

the movie was great

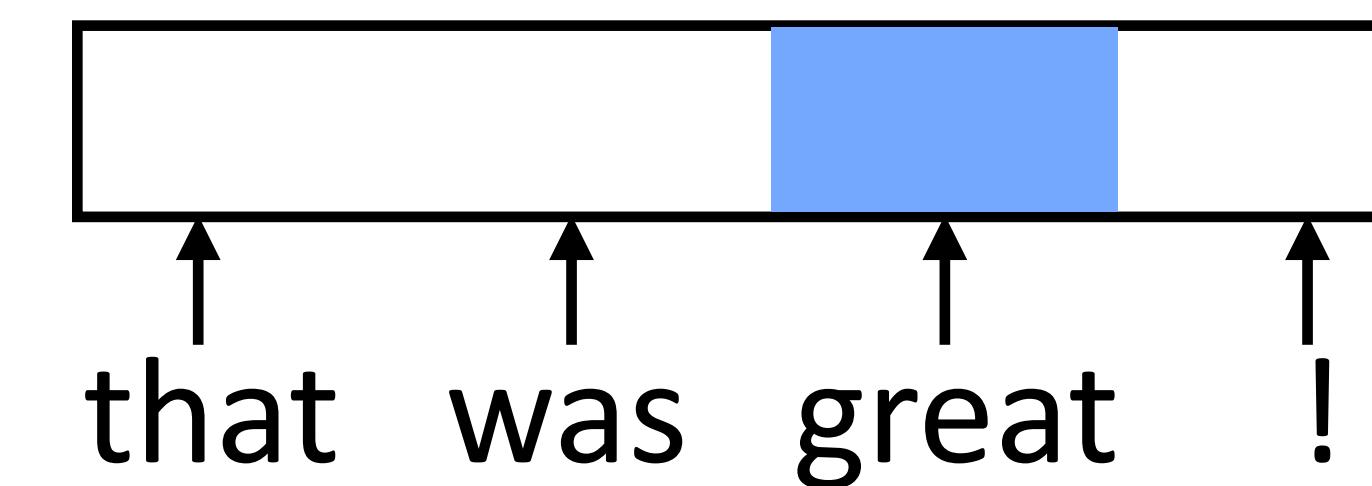
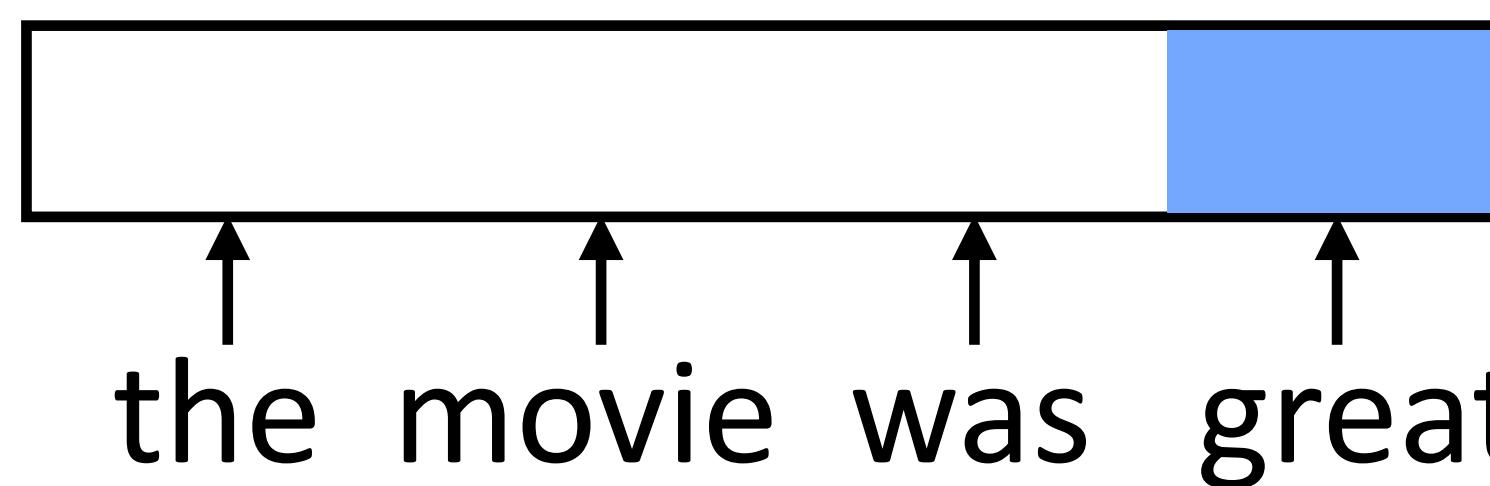
RNN Motivation

- ▶ Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics



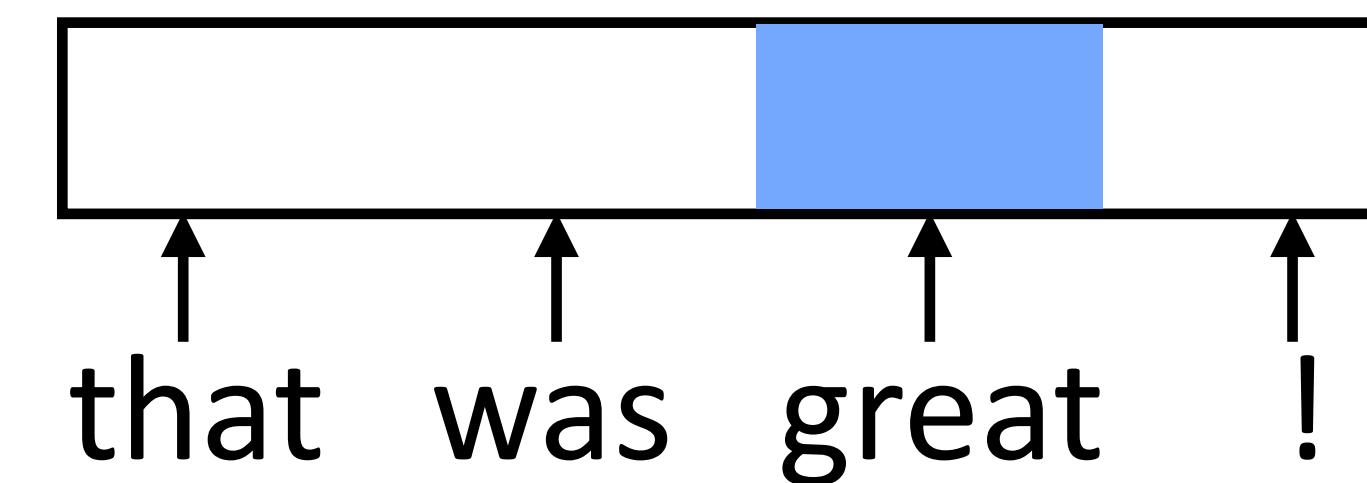
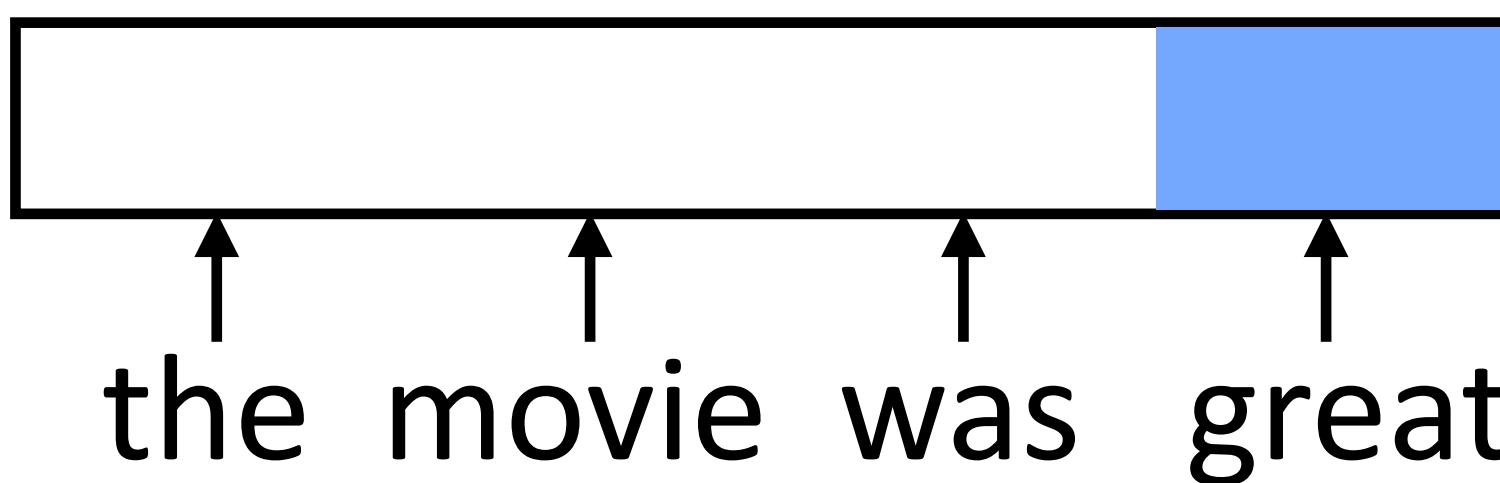
RNN Motivation

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RNN Motivation

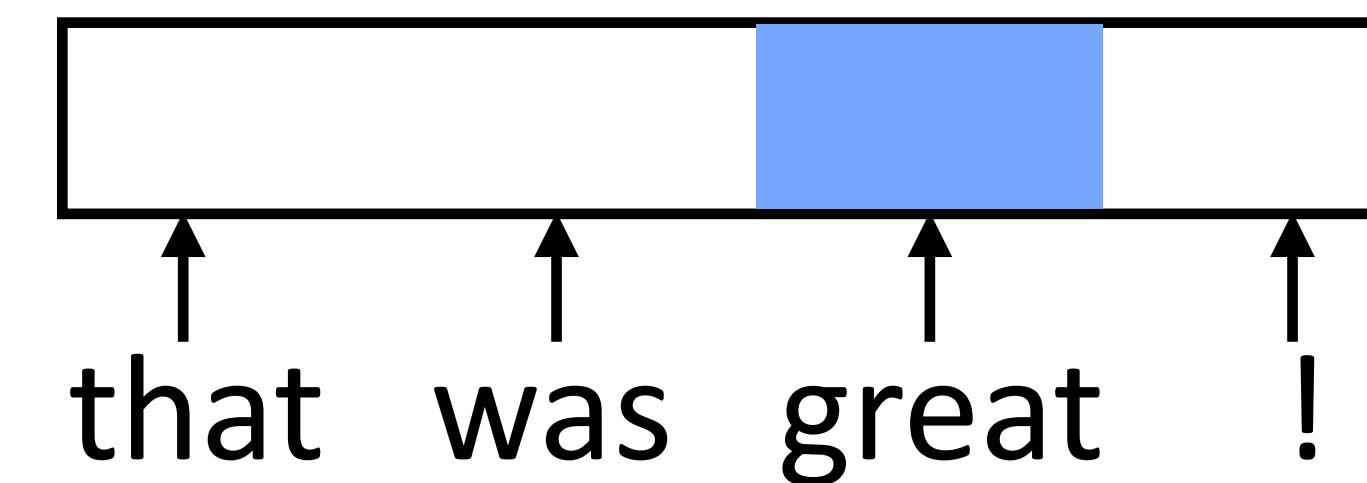
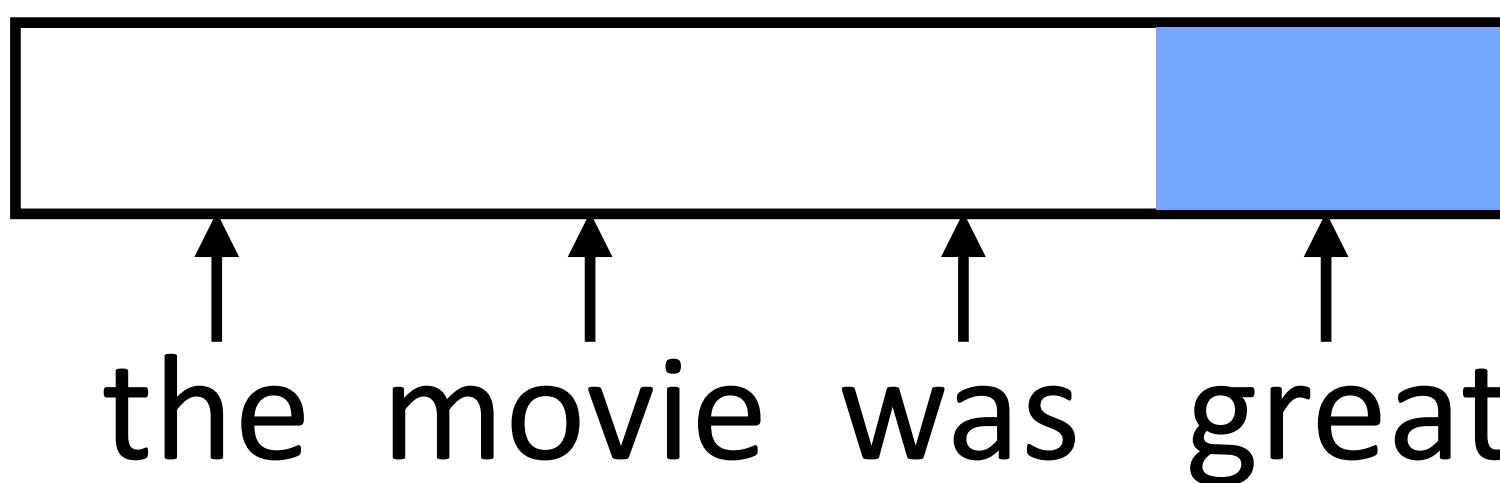
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- ▶ These don't look related (*great* is in two different orthogonal subspaces)

RNN Motivation

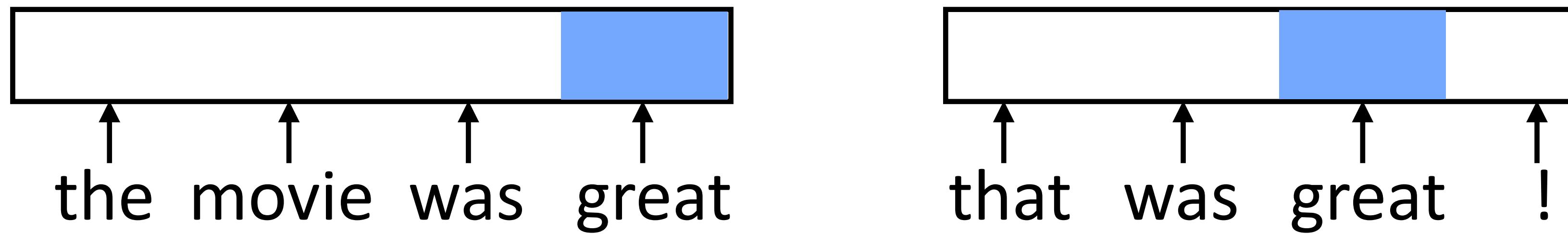
- ▶ Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics



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- ▶ Instead, we need to:

RNN Motivation

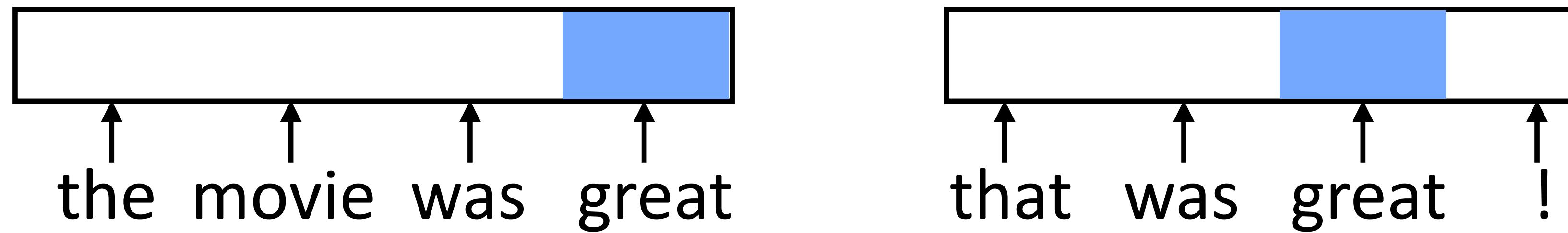
- ▶ Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics



- ▶ These don't look related (*great* is in two different orthogonal subspaces)
- ▶ Instead, we need to:
 - 1) Process each word in a uniform way

RNN Motivation

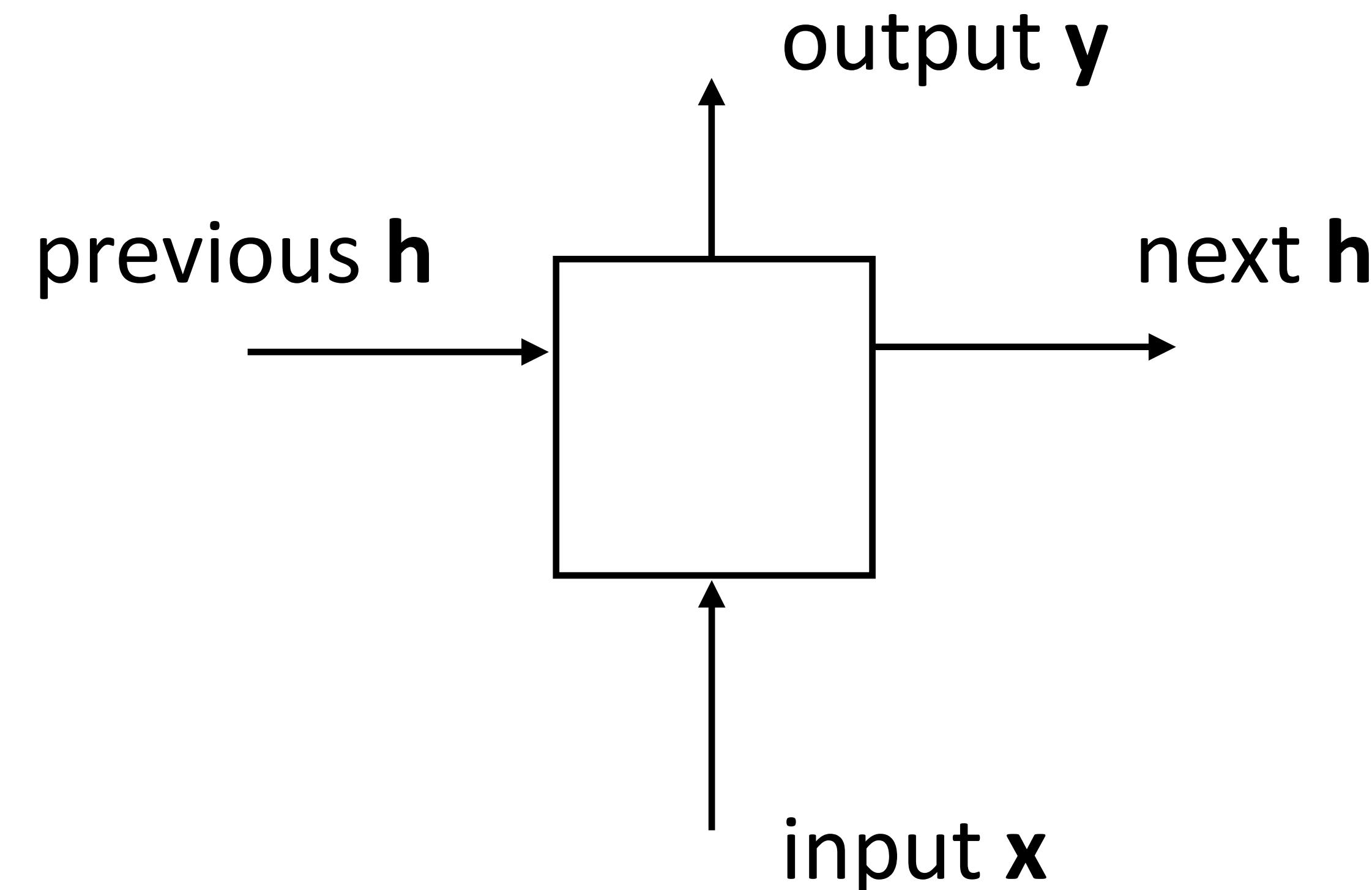
- ▶ Feedforward NNs can't handle variable length input: each position in the feature vector has fixed semantics



- ▶ These don't look related (*great* is in two different orthogonal subspaces)
- ▶ Instead, we need to:
 - 1) Process each word in a uniform way
 - 2) ...while still exploiting the context that that token occurs in

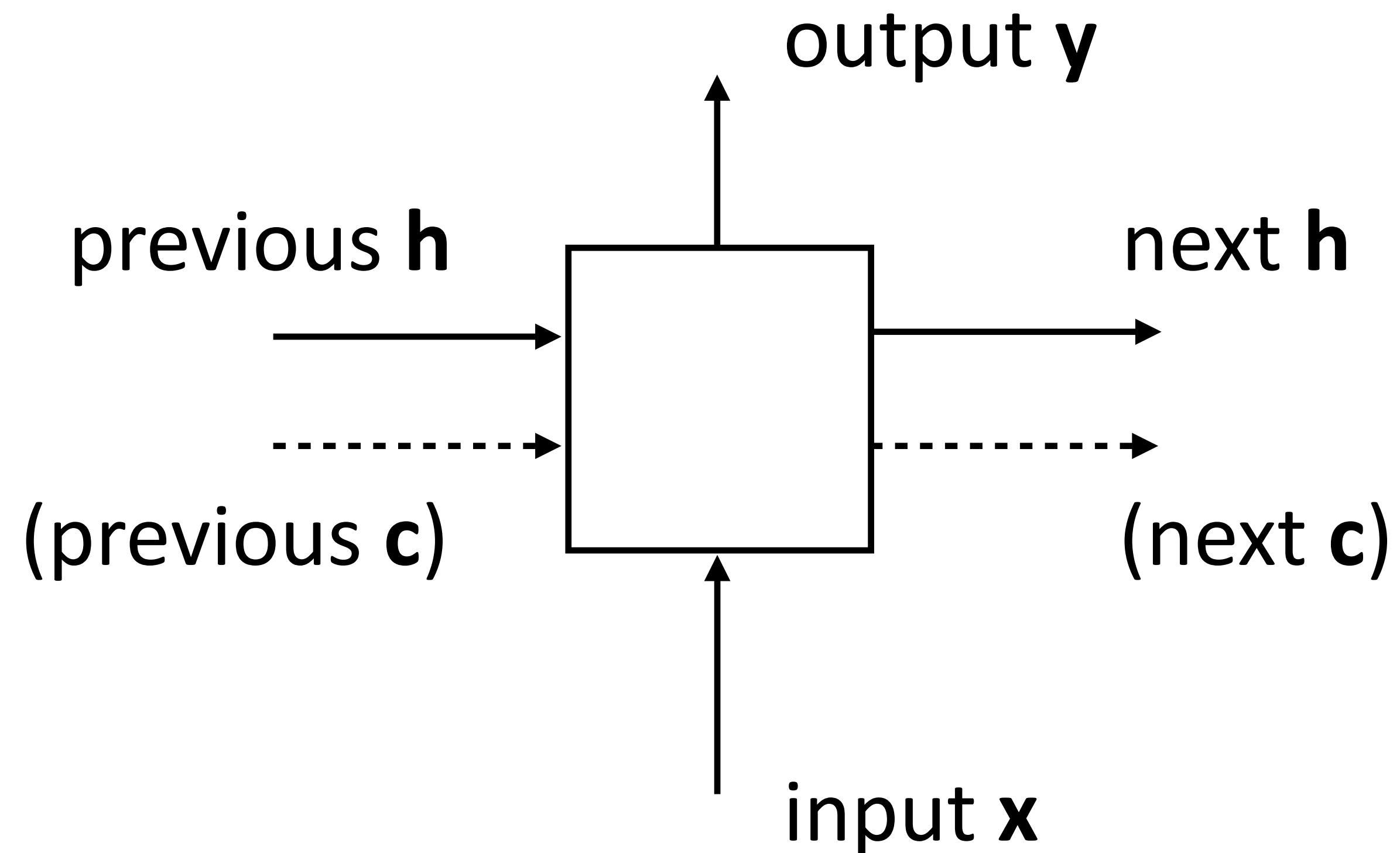
RNN Abstraction

- ▶ Cell that takes some input x , has some hidden state h , and updates that hidden state and produces output y (all vector-valued)



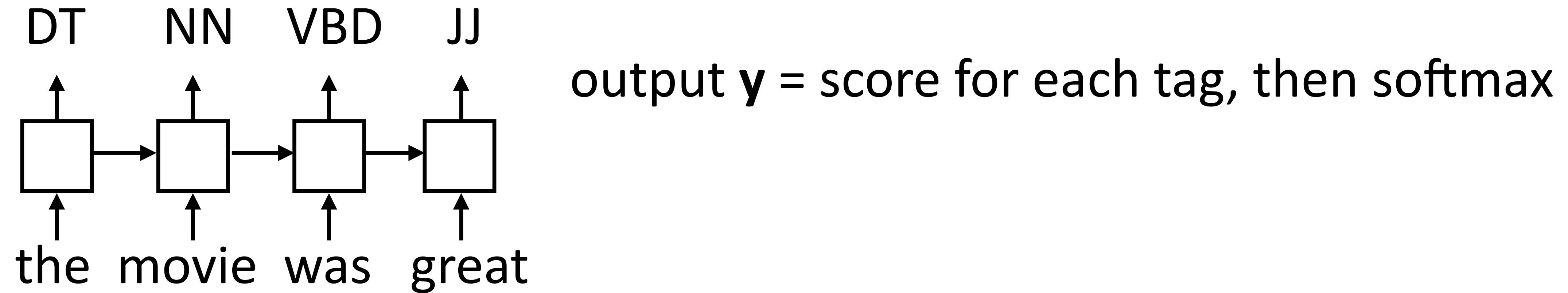
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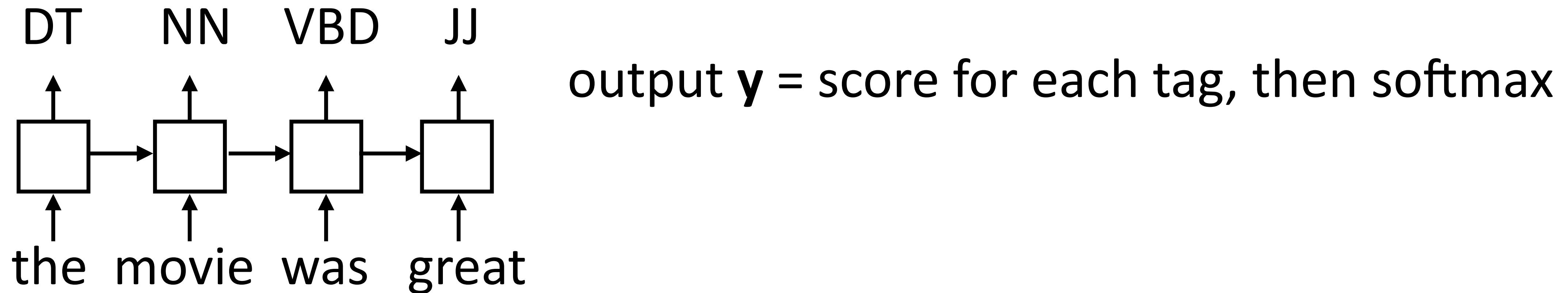
RNN Uses

- ▶ Transducer: make some prediction for each element in a sequence

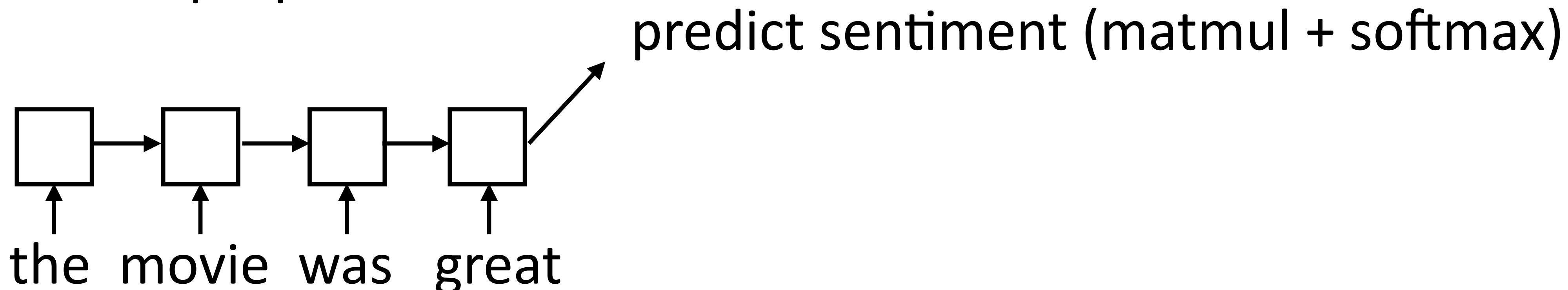


RNN Uses

- ▶ Transducer: make some prediction for each element in a sequence

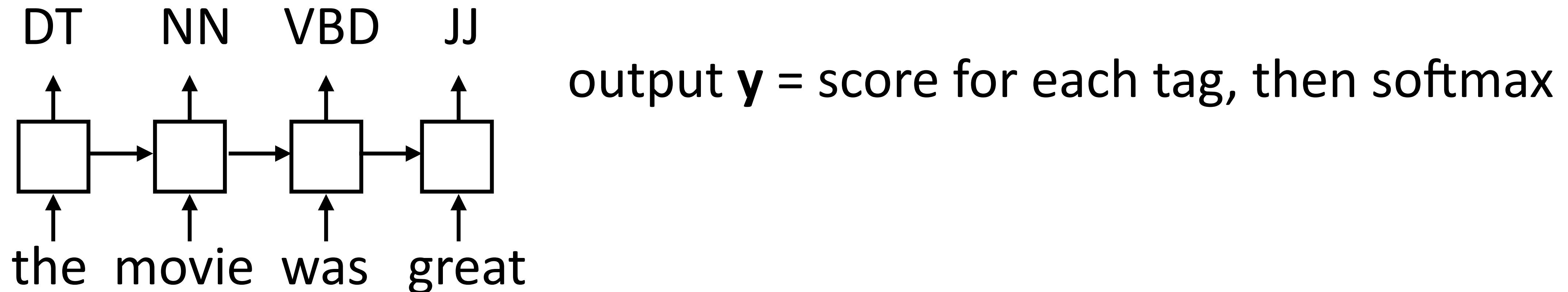


- ▶ Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose

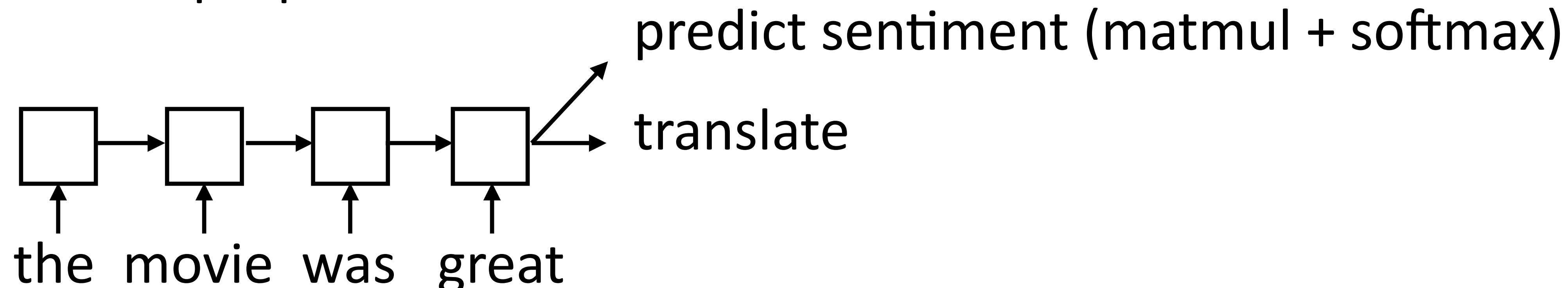


RNN Uses

- ▶ Transducer: make some prediction for each element in a sequence

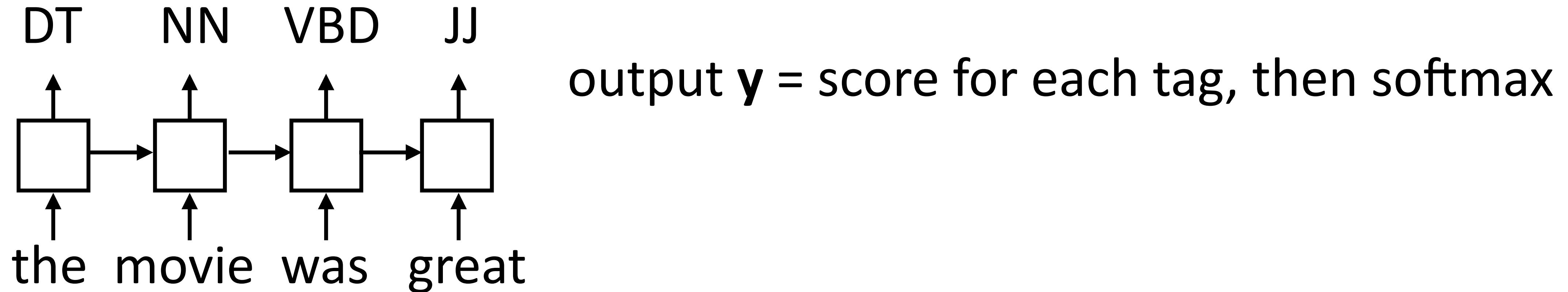


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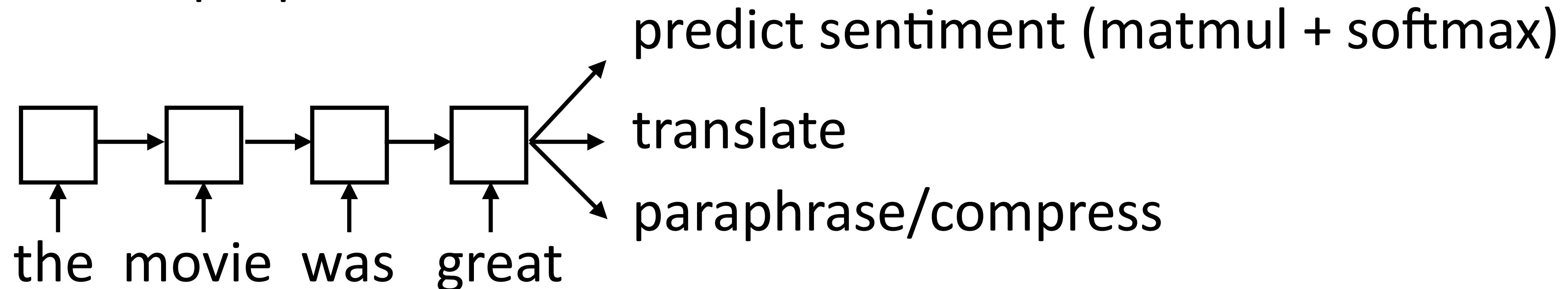


RNN Uses

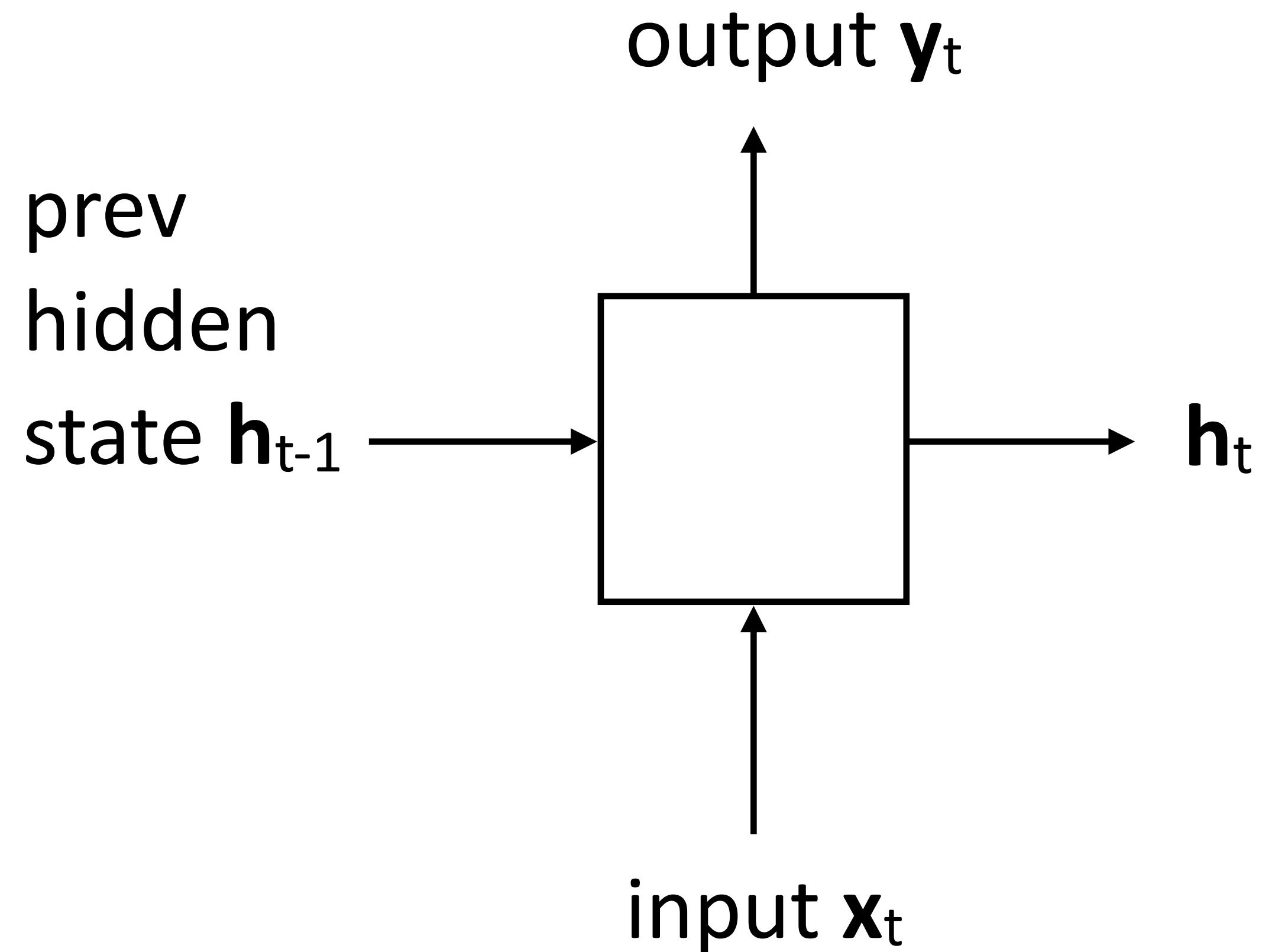
- ▶ Transducer: make some prediction for each element in a sequence



- ▶ Acceptor/encoder: encode a sequence into a fixed-sized vector and use that for some purpose

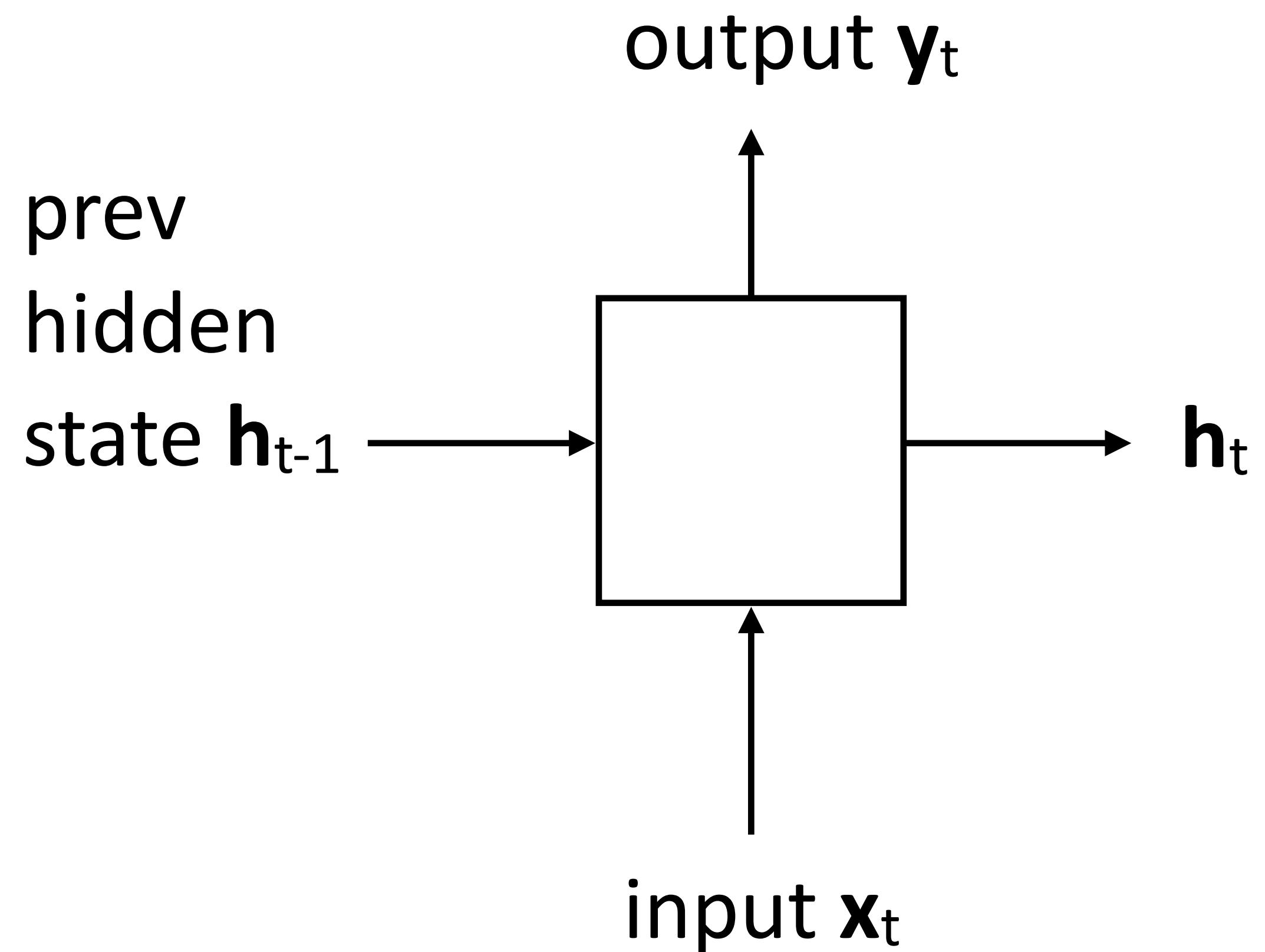


Elman Networks



Elman (1990)

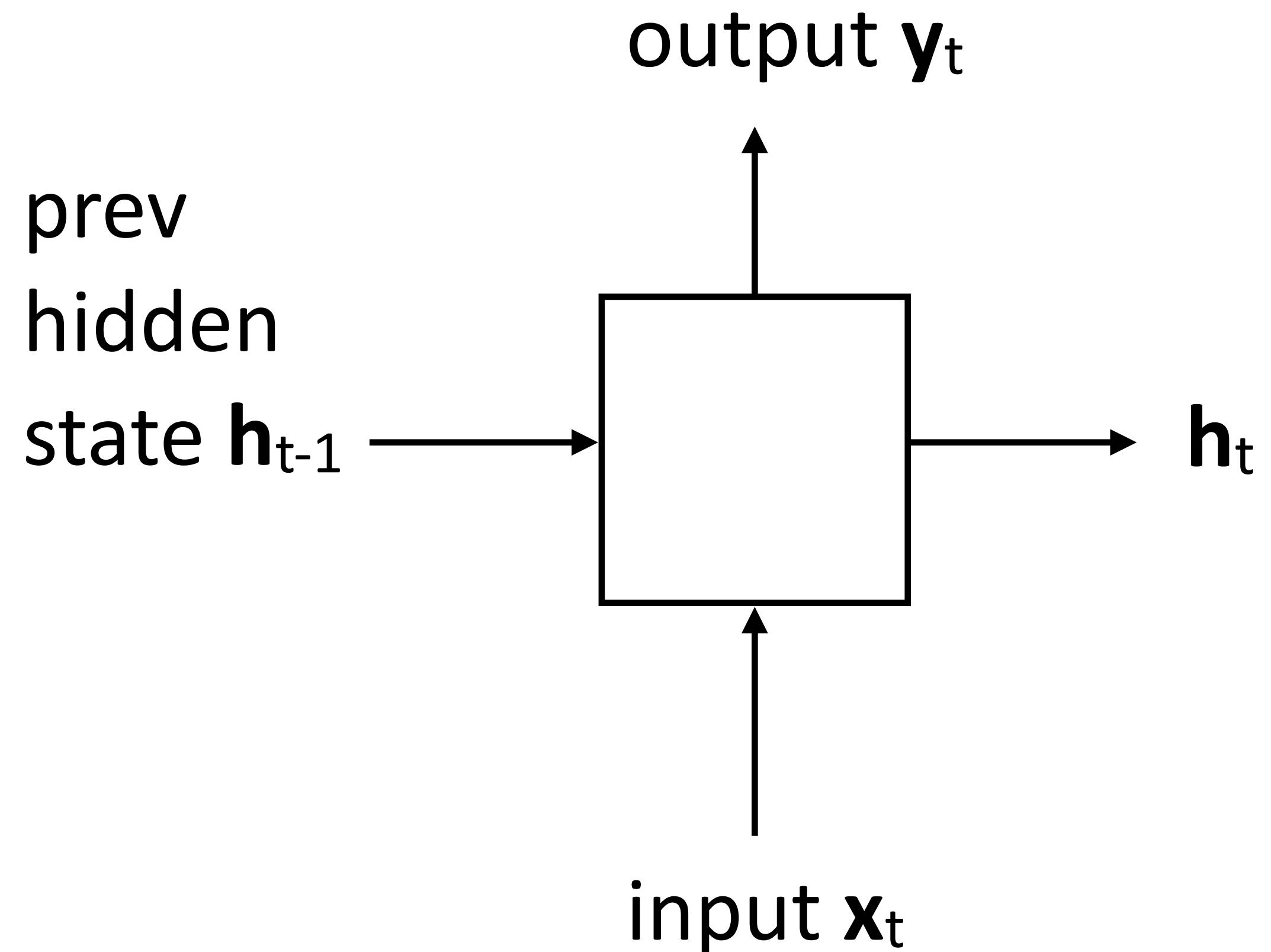
Elman Networks



$$h_t = \tanh(Wx_t + Vh_{t-1} + b_h)$$

- ▶ Updates hidden state based on input and current hidden state

Elman Networks



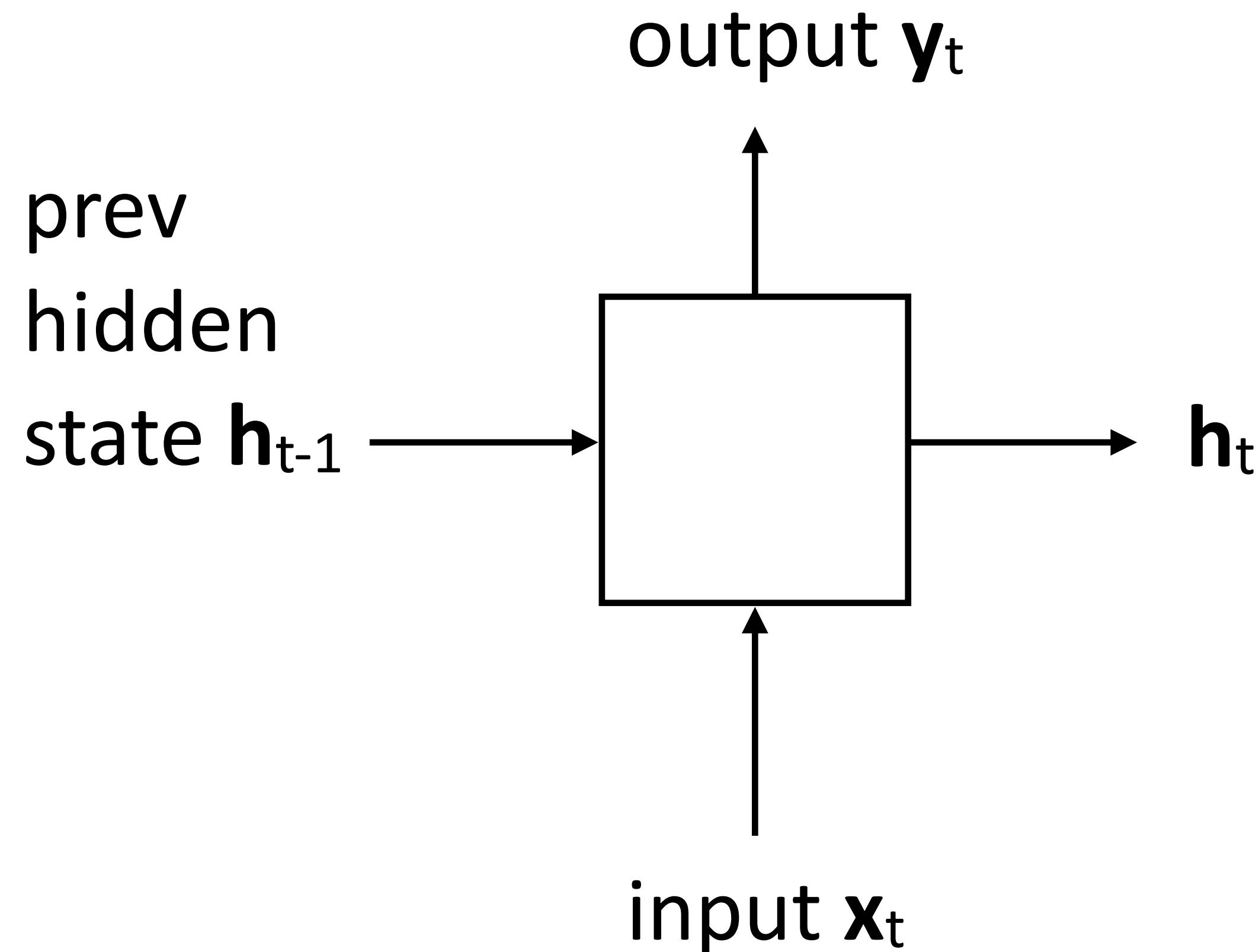
$$h_t = \tanh(Wx_t + Vh_{t-1} + b_h)$$

- ▶ Updates hidden state based on input and current hidden state

$$y_t = \tanh(Uh_t + b_y)$$

- ▶ Computes output from hidden state

Elman Networks



$$h_t = \tanh(Wx_t + Vh_{t-1} + b_h)$$

- ▶ Updates hidden state based on input and current hidden state

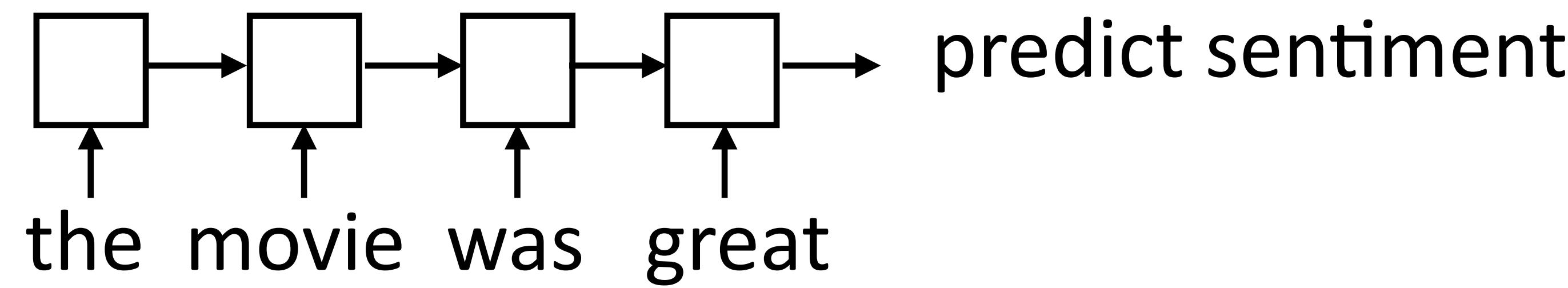
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- ▶ Computes output from hidden state

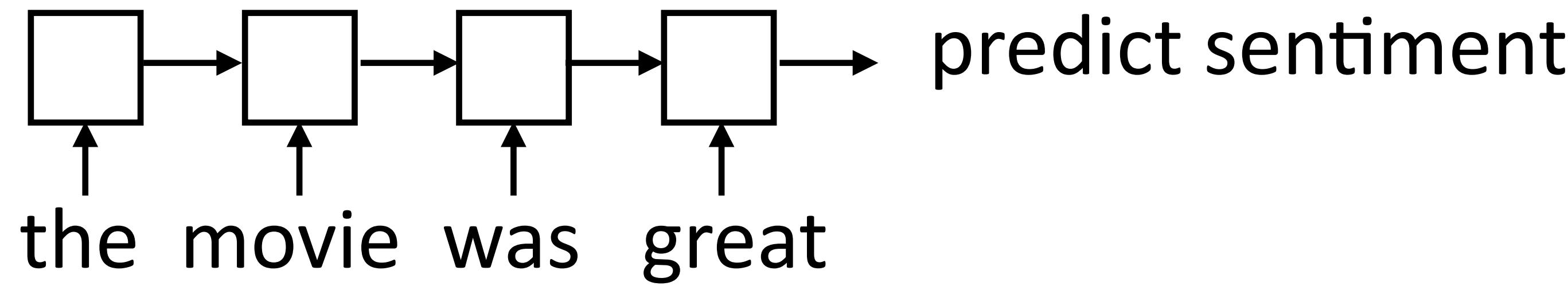
- ▶ Long history! (invented in the late 1980s)

Elman (1990)

Training Elman Networks

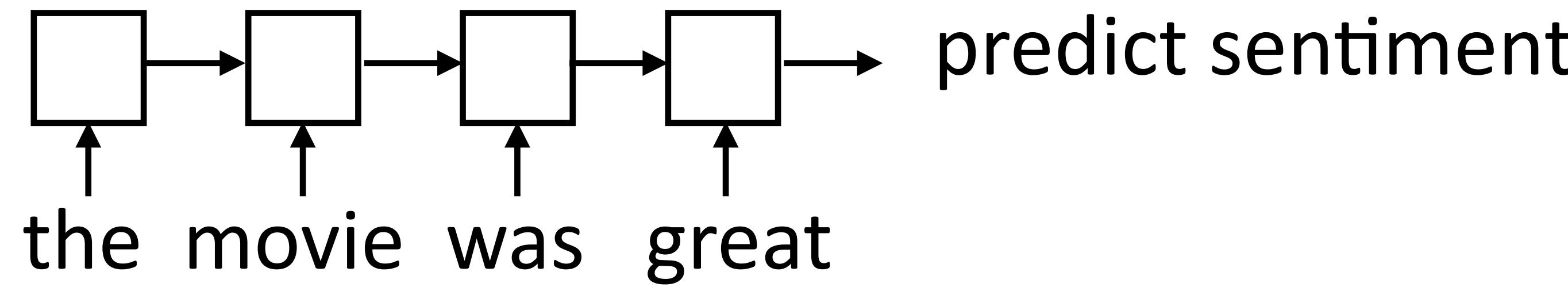


Training Elman Networks



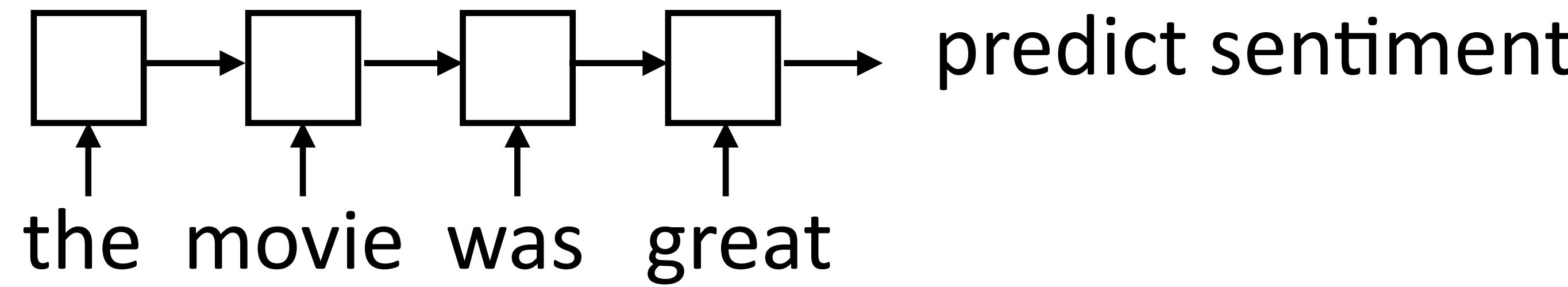
- ▶ “Backpropagation through time”: build the network as one big computation graph, some parameters are shared

Training Elman Networks



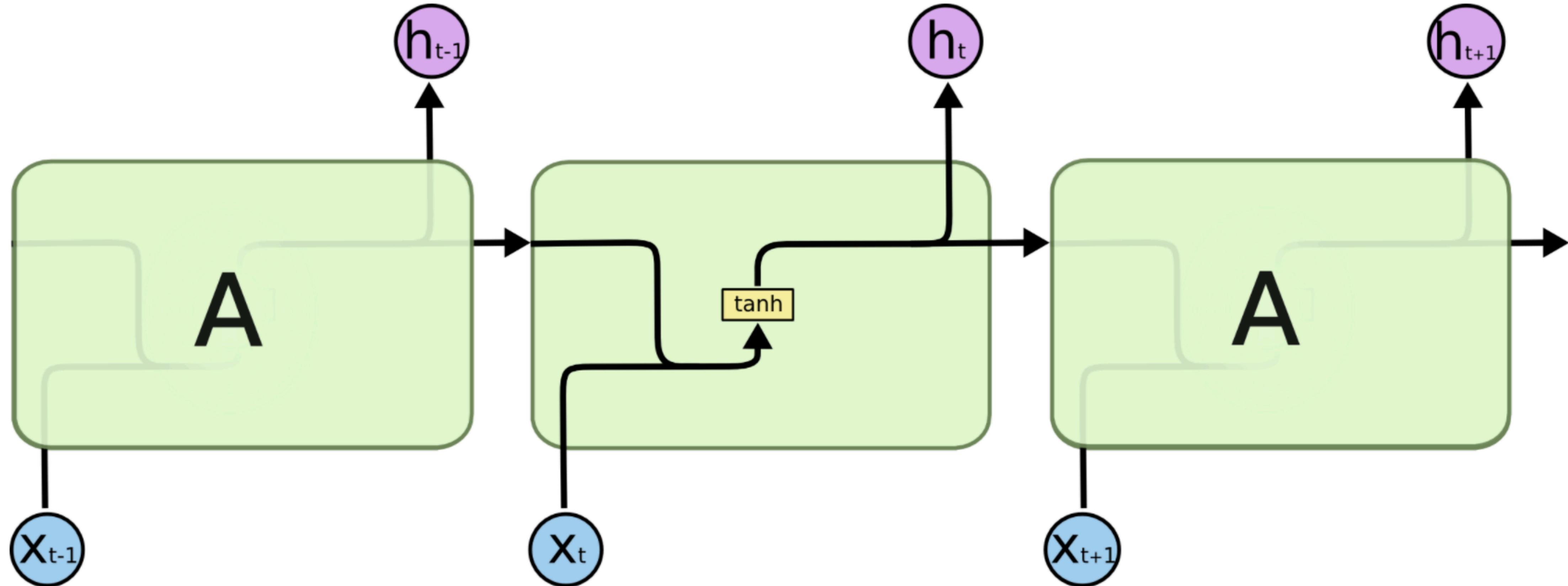
- ▶ “Backpropagation through time”: build the network as one big computation graph, some parameters are shared
 - ▶ RNN potentially needs to learn how to “remember” information for a long time!
- it was my **favorite** movie of 2016, though it wasn’t without **problems** -> +

Training Elman Networks

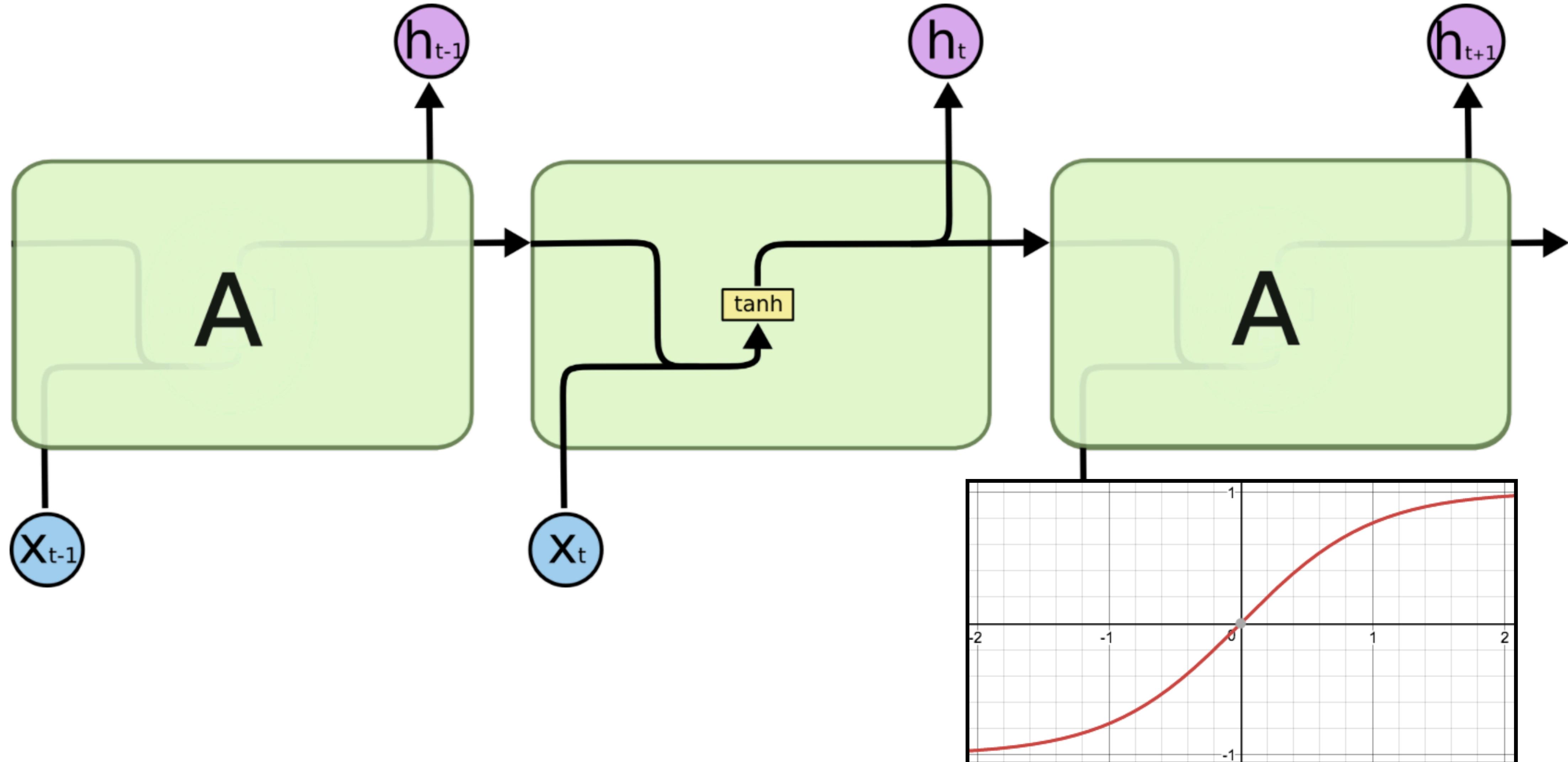


- ▶ “Backpropagation through time”: build the network as one big computation graph, some parameters are shared
 - ▶ RNN potentially needs to learn how to “remember” information for a long time!
- it was my **favorite** movie of 2016, though it wasn’t without **problems** -> +
- ▶ “Correct” parameter update is to do a better job of remembering the sentiment of *favorite*

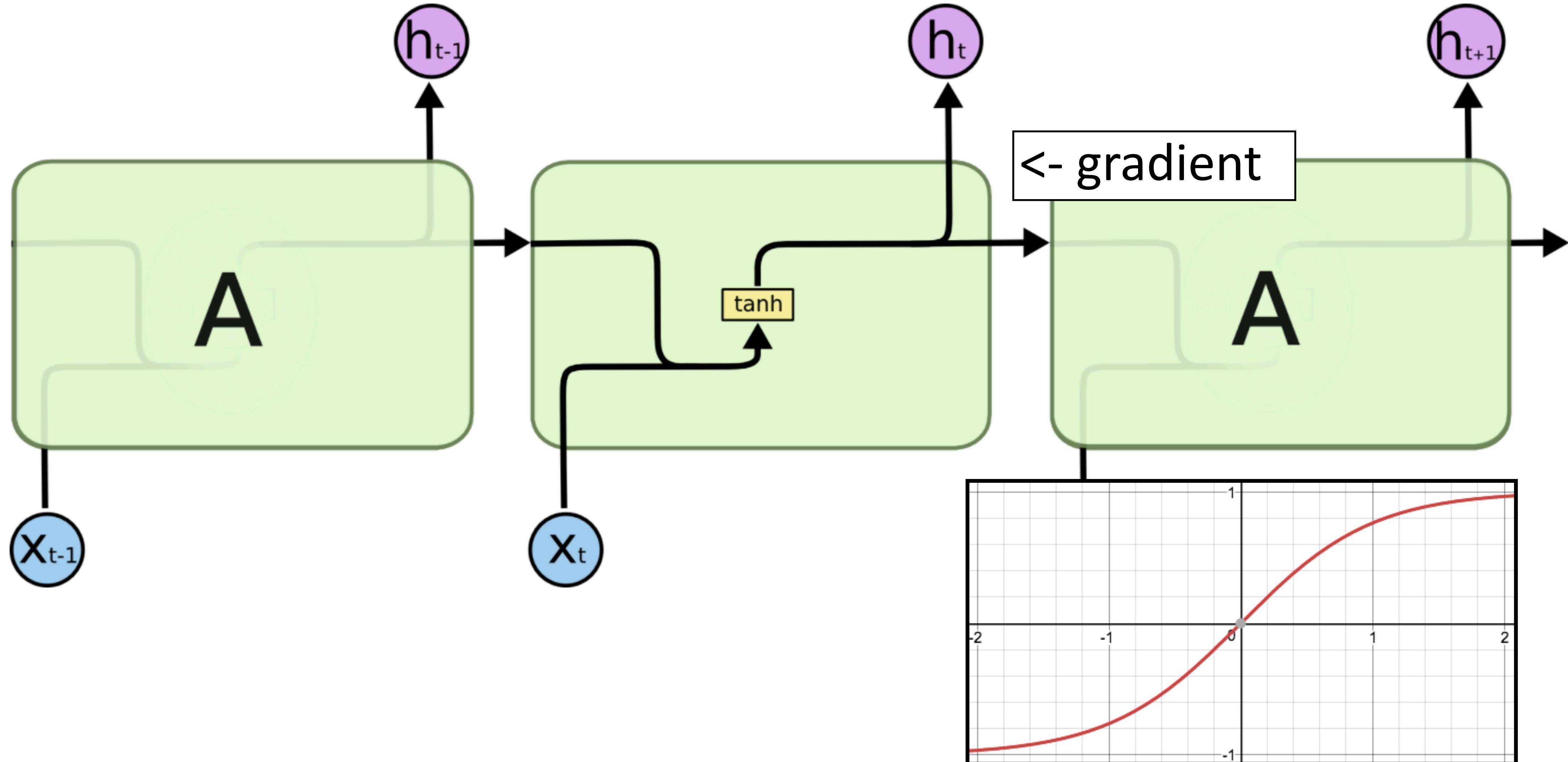
Vanishing Gradient



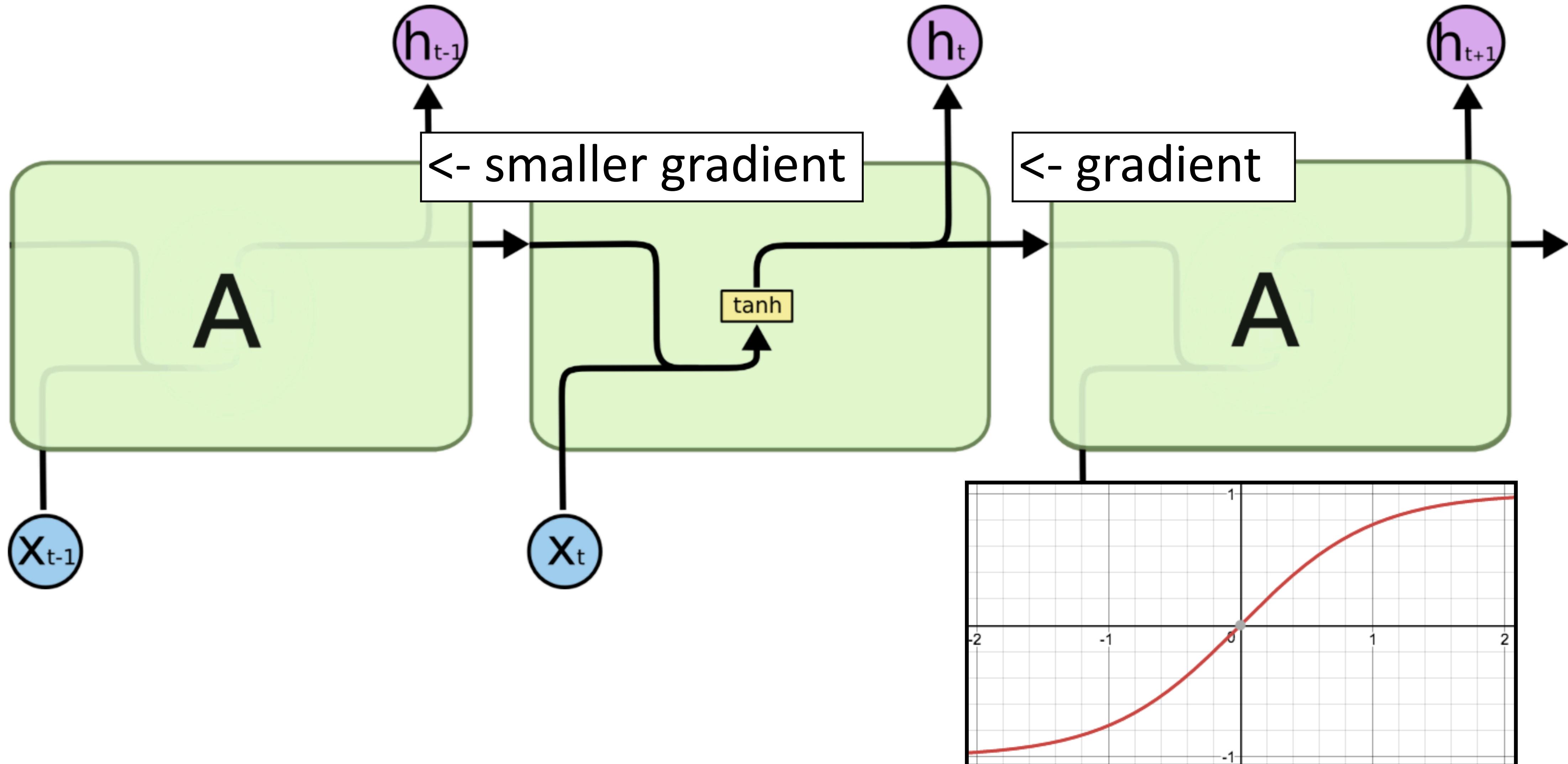
Vanishing Gradient



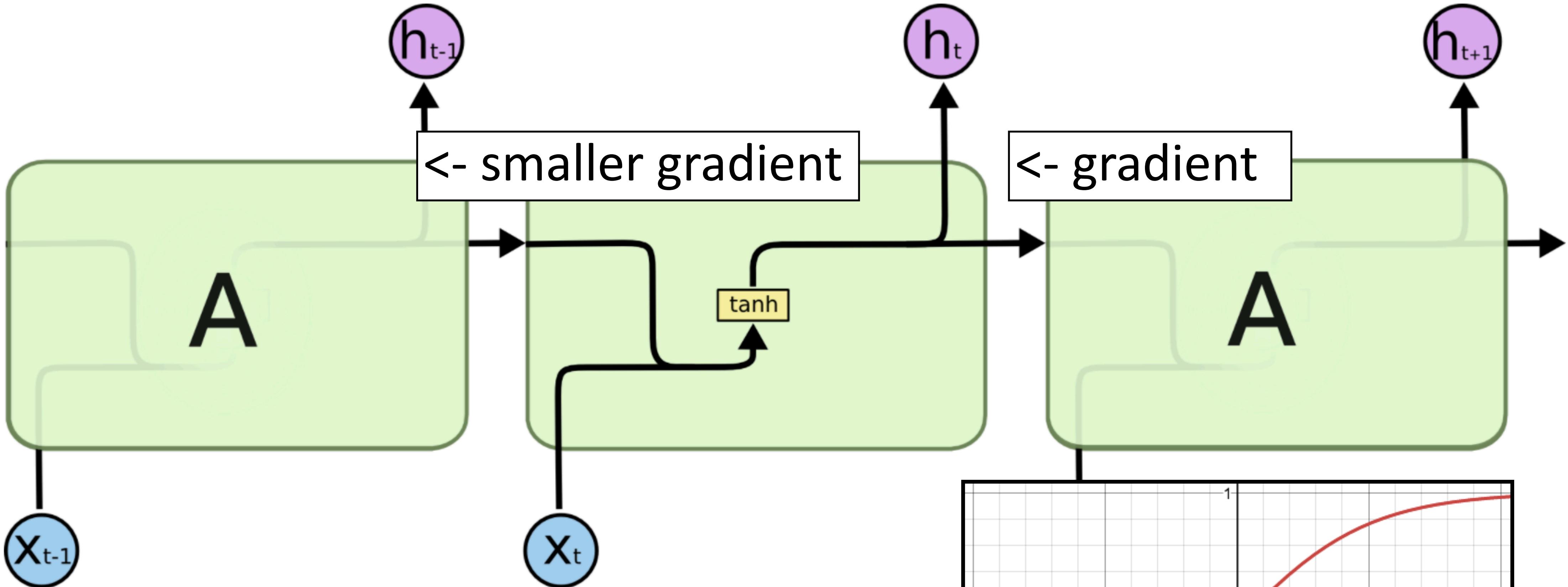
Vanishing Gradient



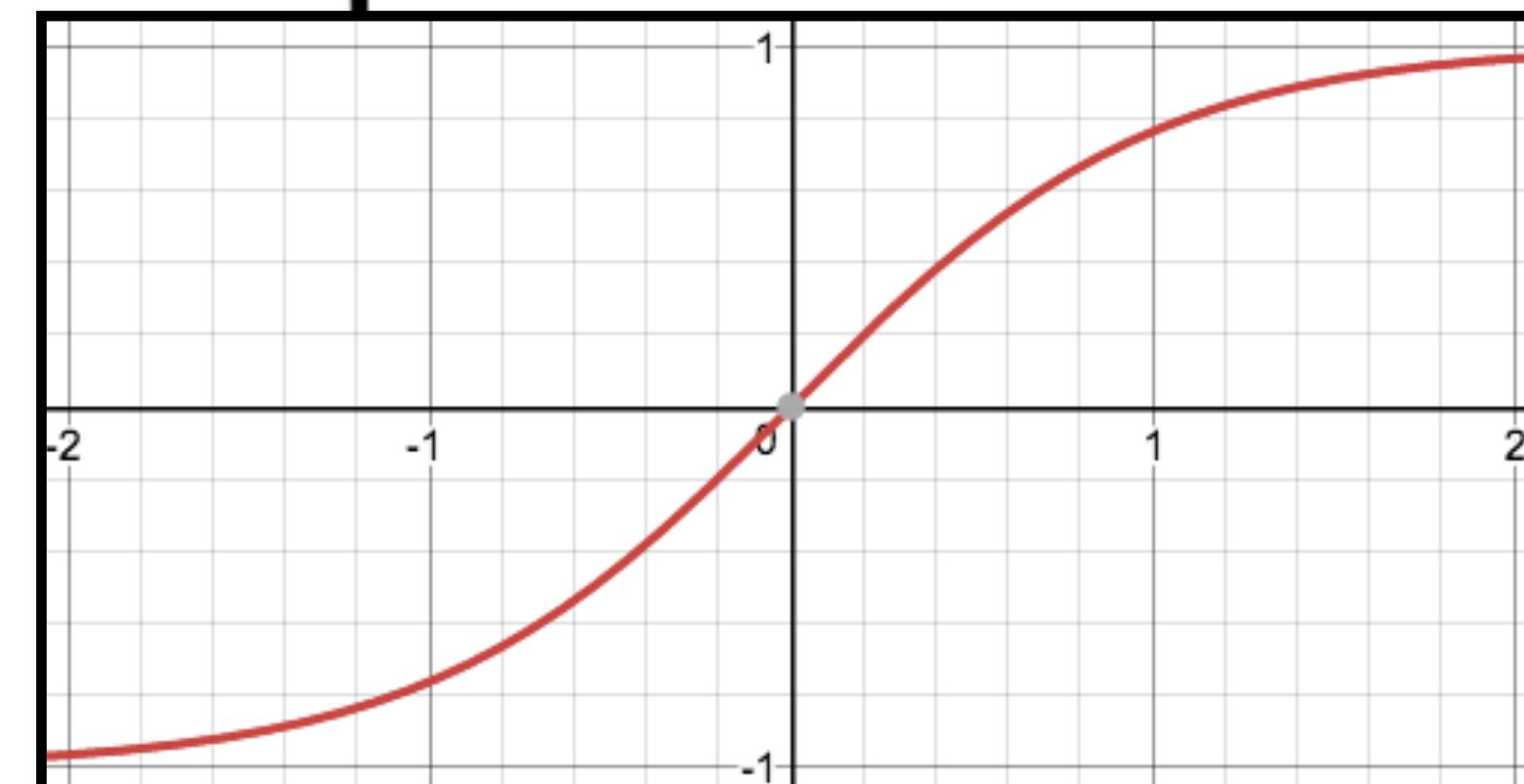
Vanishing Gradient



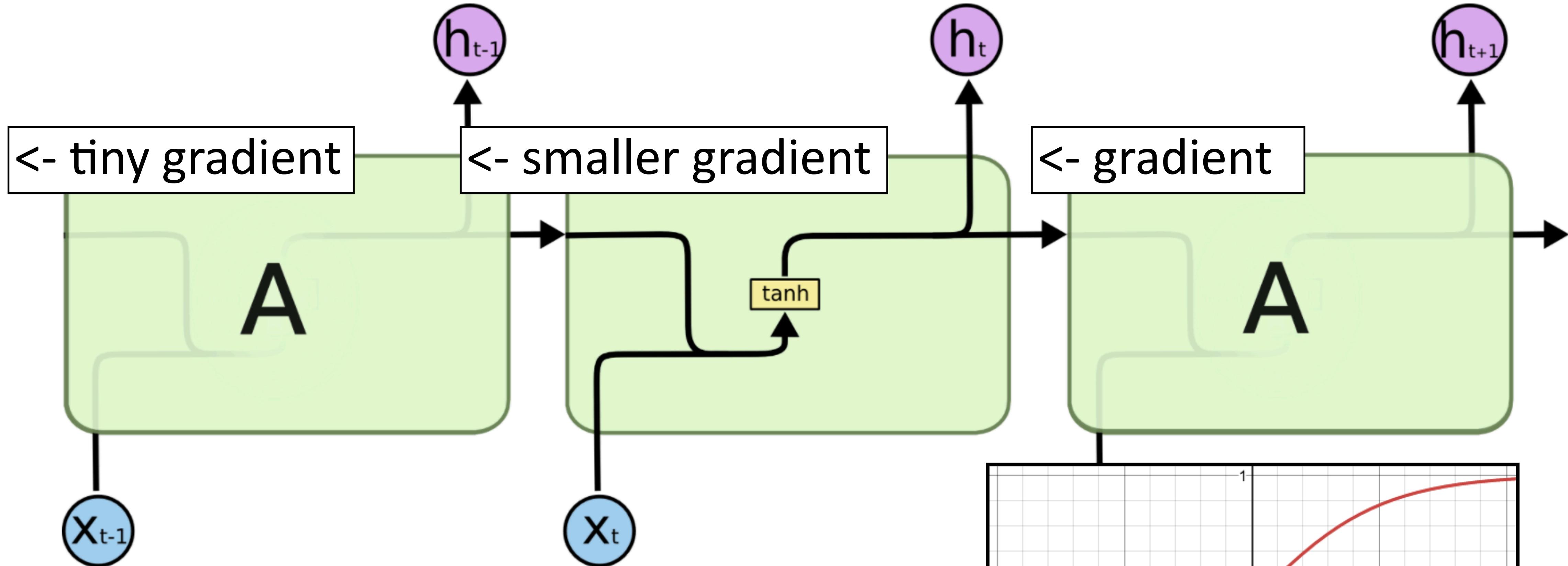
Vanishing Gradient



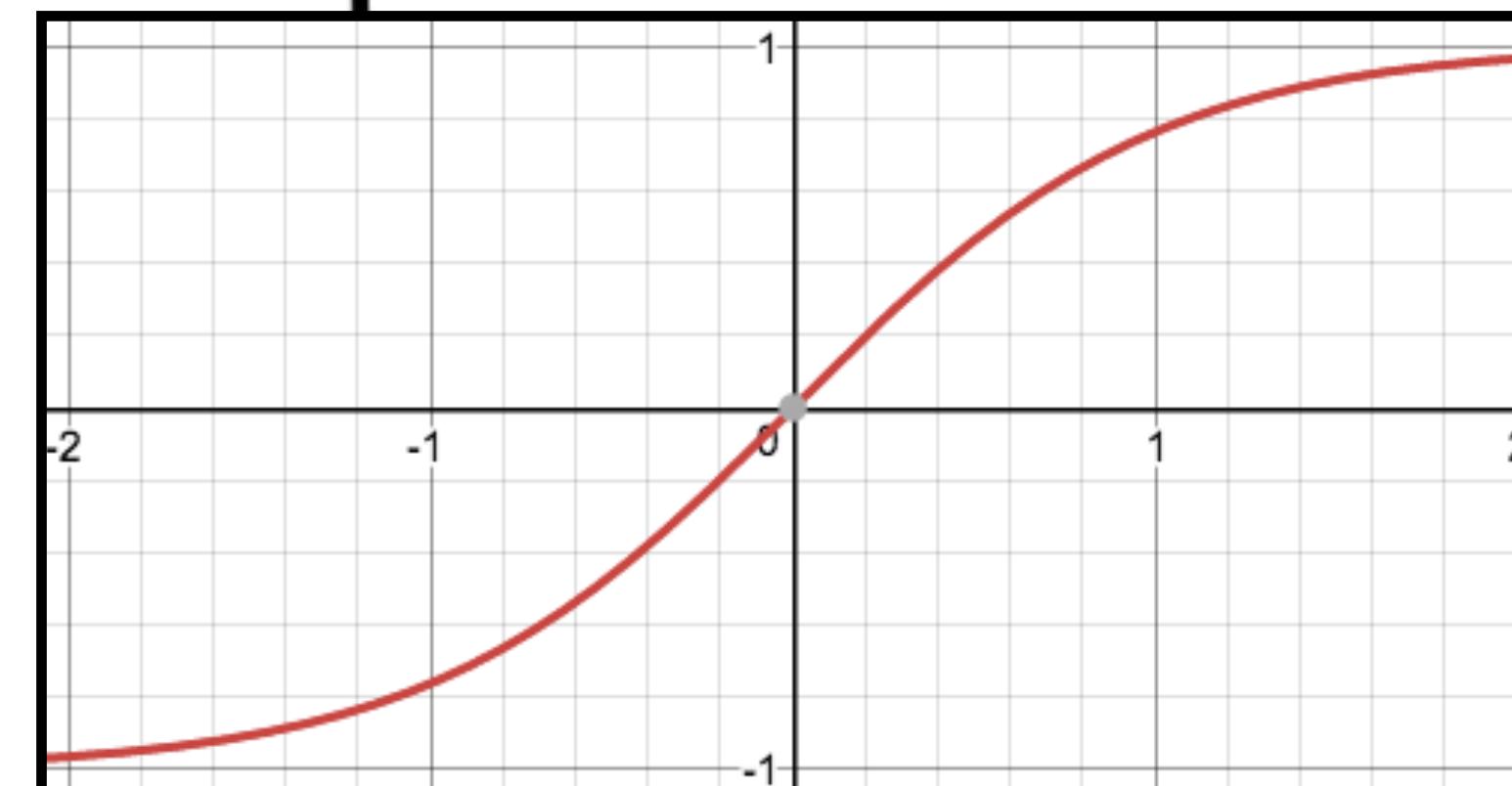
- ▶ Gradient diminishes going through tanh; if not in $[-2, 2]$, gradient is almost 0



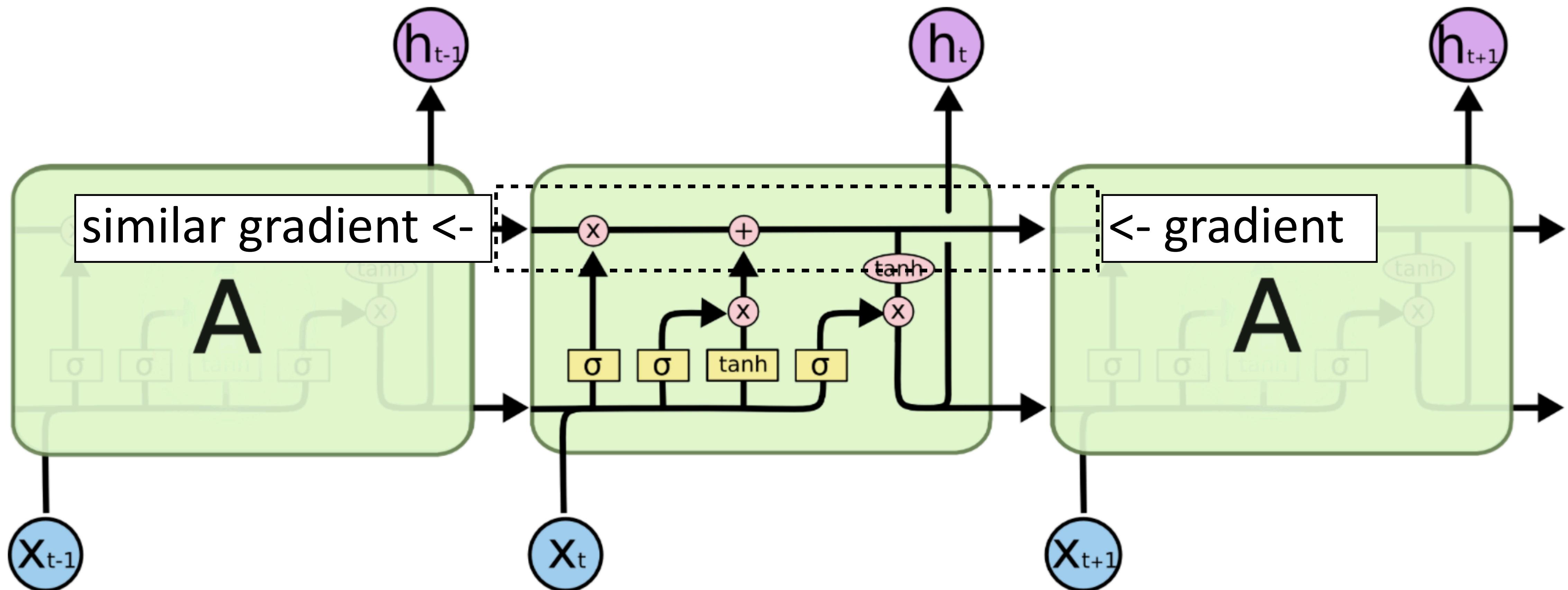
Vanishing Gradient



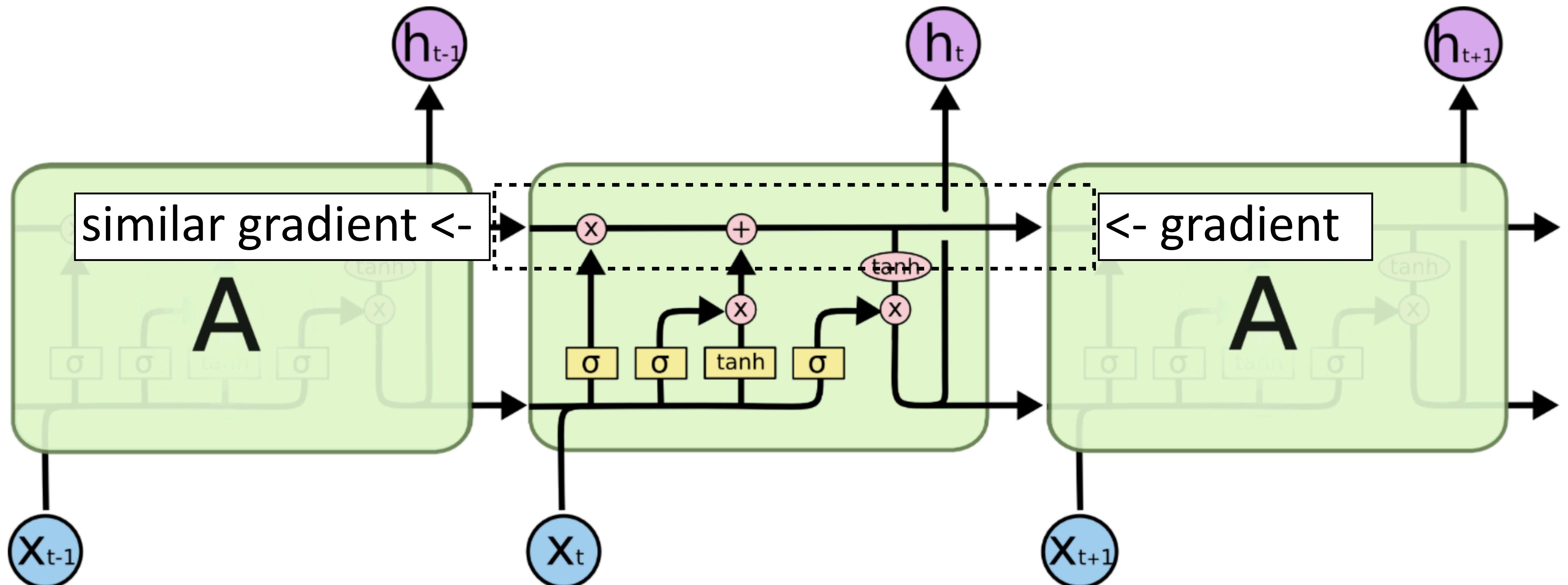
- ▶ Gradient diminishes going through tanh; if not in $[-2, 2]$, gradient is almost 0



LSTMs

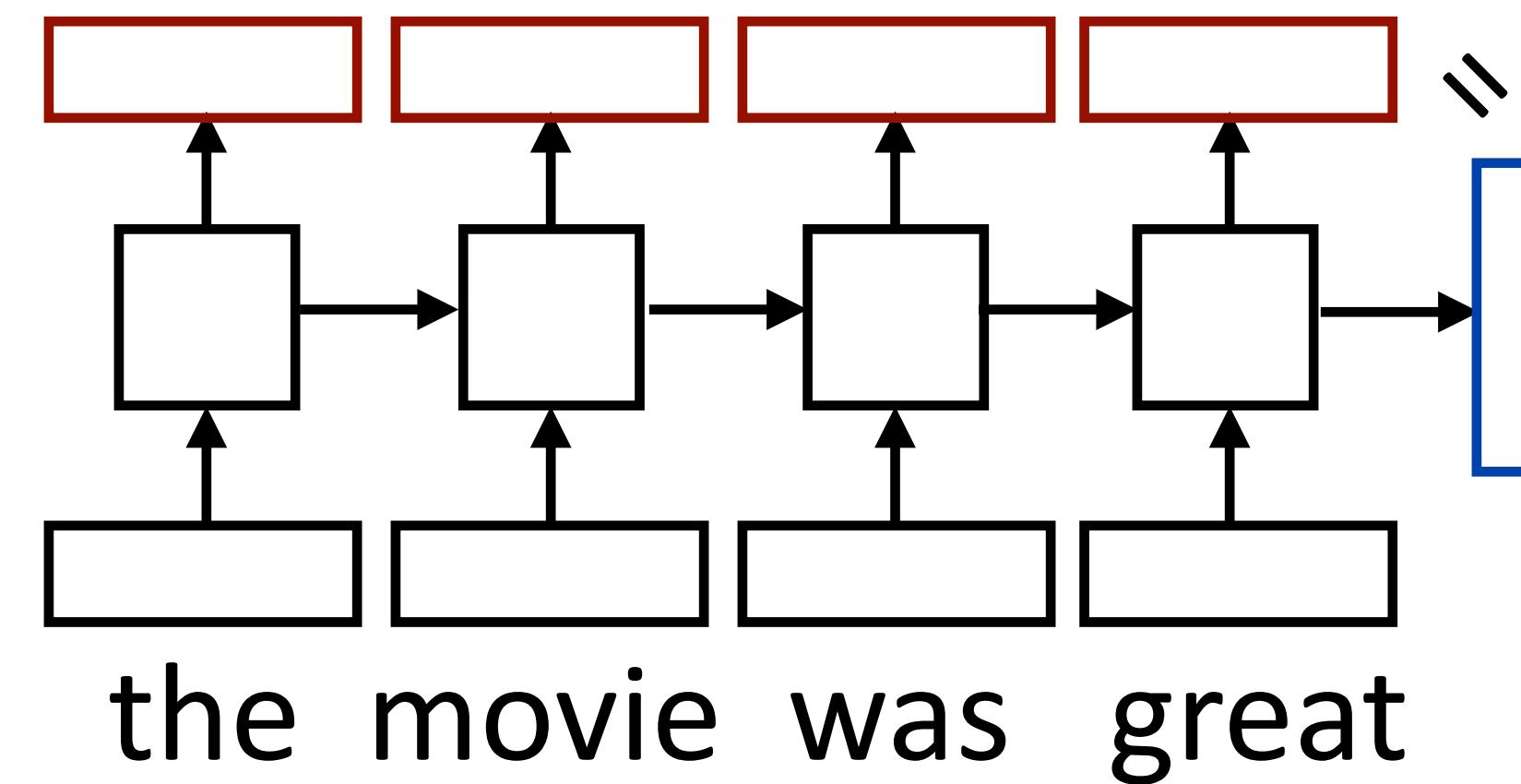


LSTMs



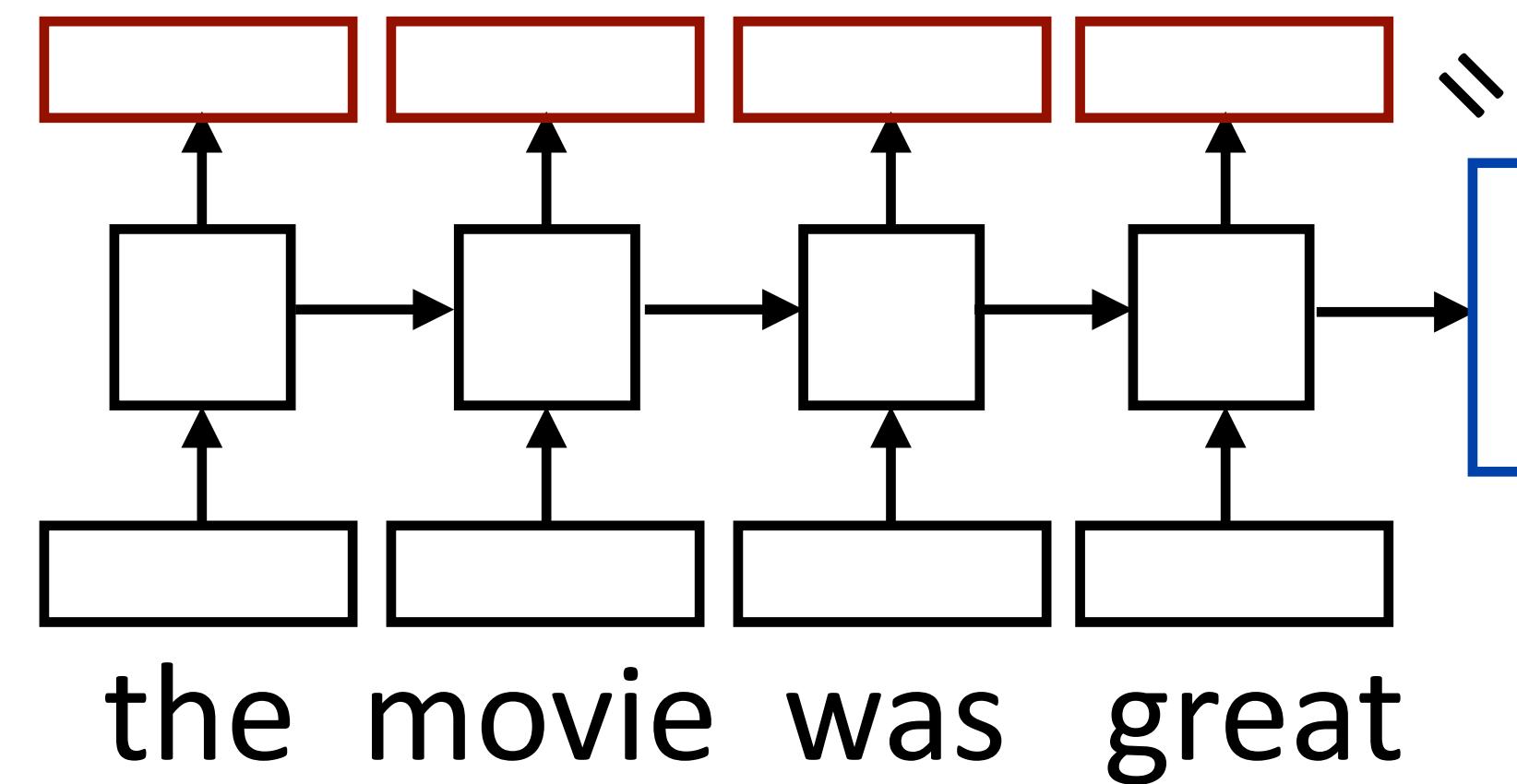
- ▶ Gradient still diminishes, but in a controlled way and generally by less — usually initialize forget gate = 1 to remember everything to start

What do RNNs produce?



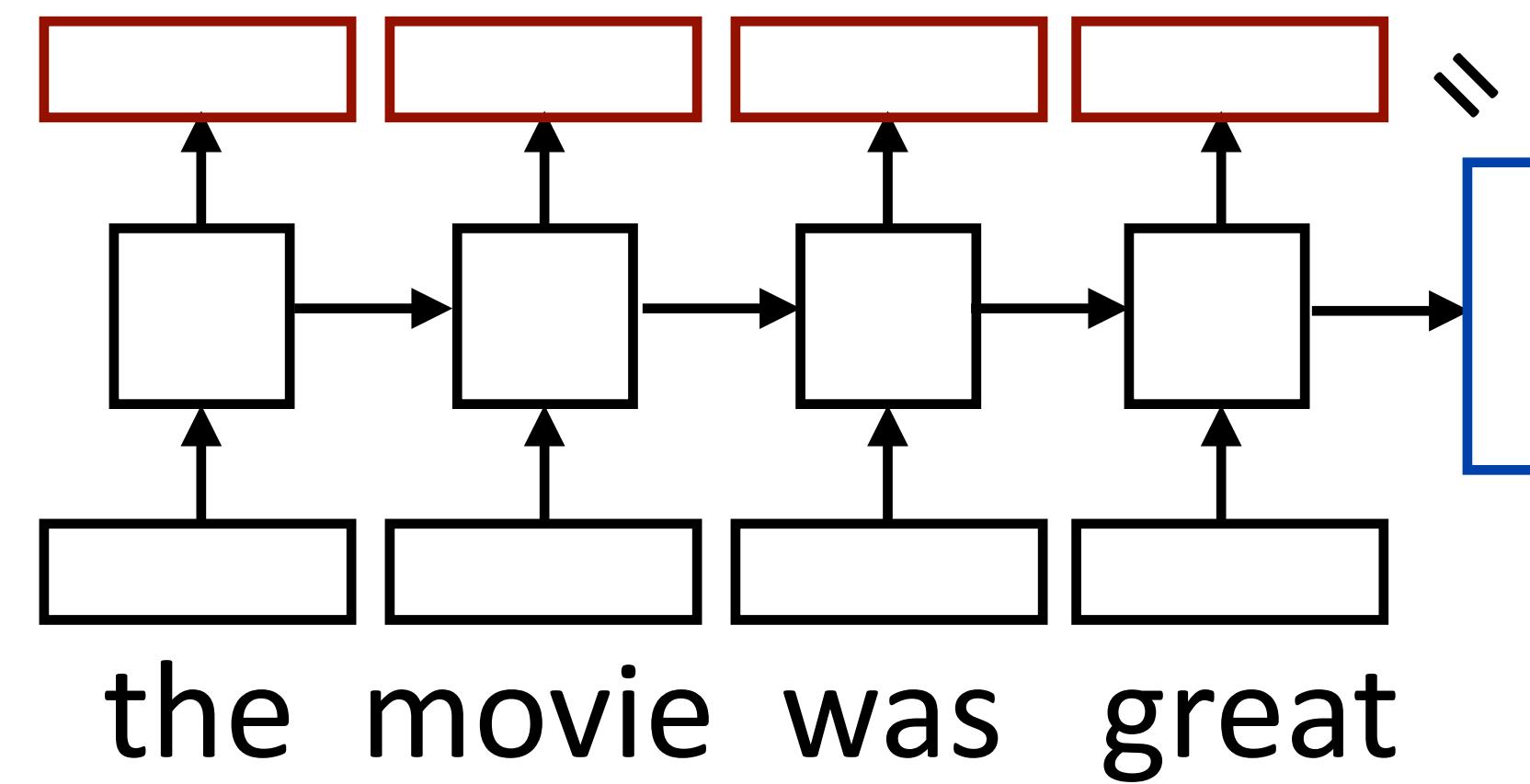
- ▶ **Encoding of the sentence** – can pass this a decoder or make a classification decision about the sentence

What do RNNs produce?



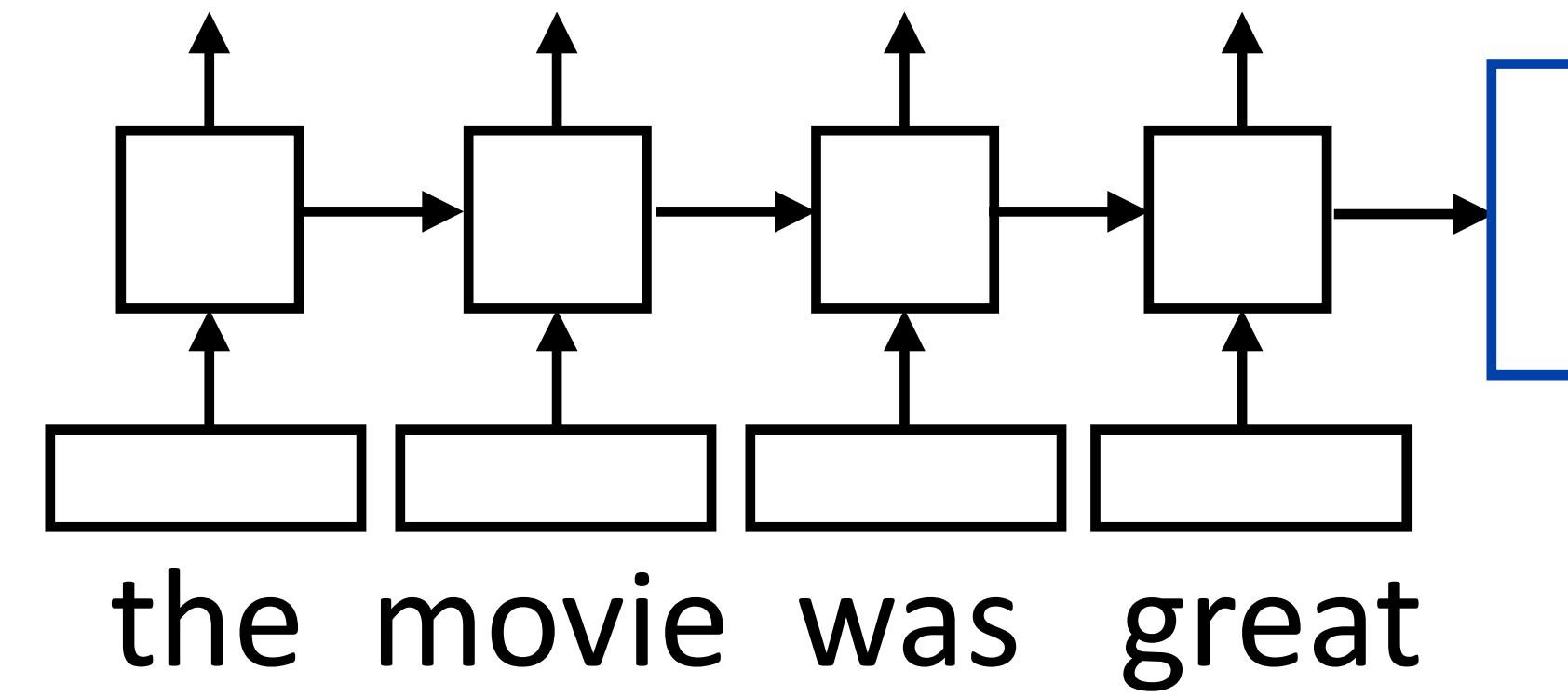
- ▶ **Encoding of the sentence** – can pass this to a decoder or make a classification decision about the sentence
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What do RNNs produce?

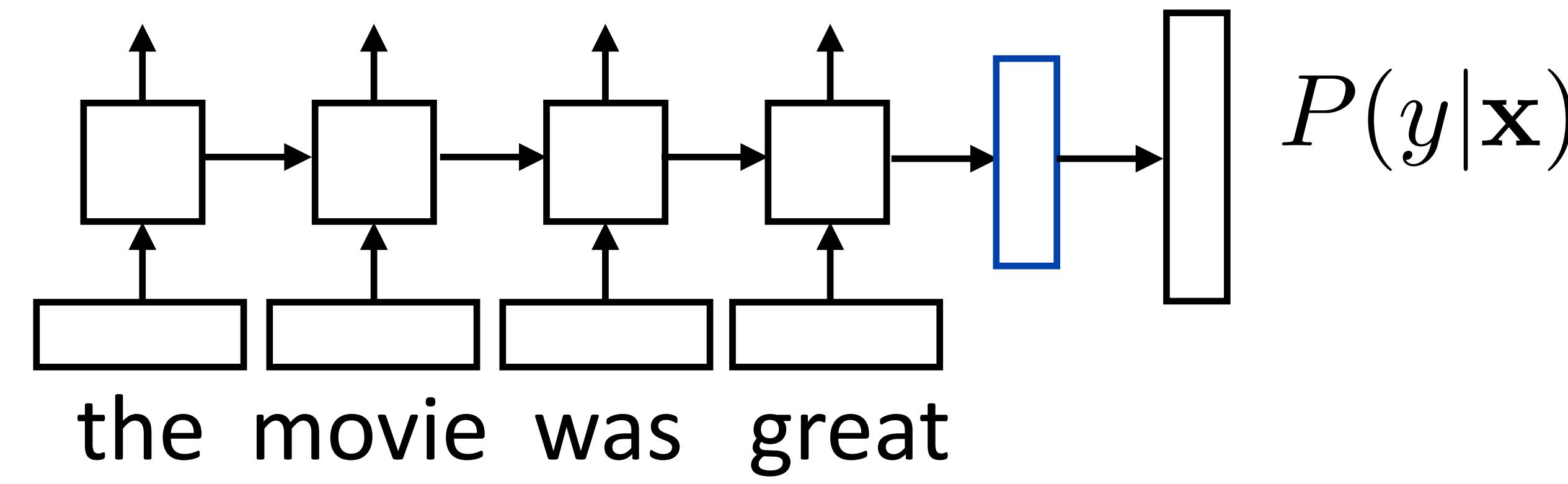


- ▶ **Encoding of the sentence** – can pass this a decoder or make a classification decision about the sentence
- ▶ **Encoding of each word** – can pass this to another layer to make a prediction (can also pool these to get a different sentence encoding)
- ▶ RNN can be viewed as a transformation of a sequence of vectors into a sequence of context-dependent vectors

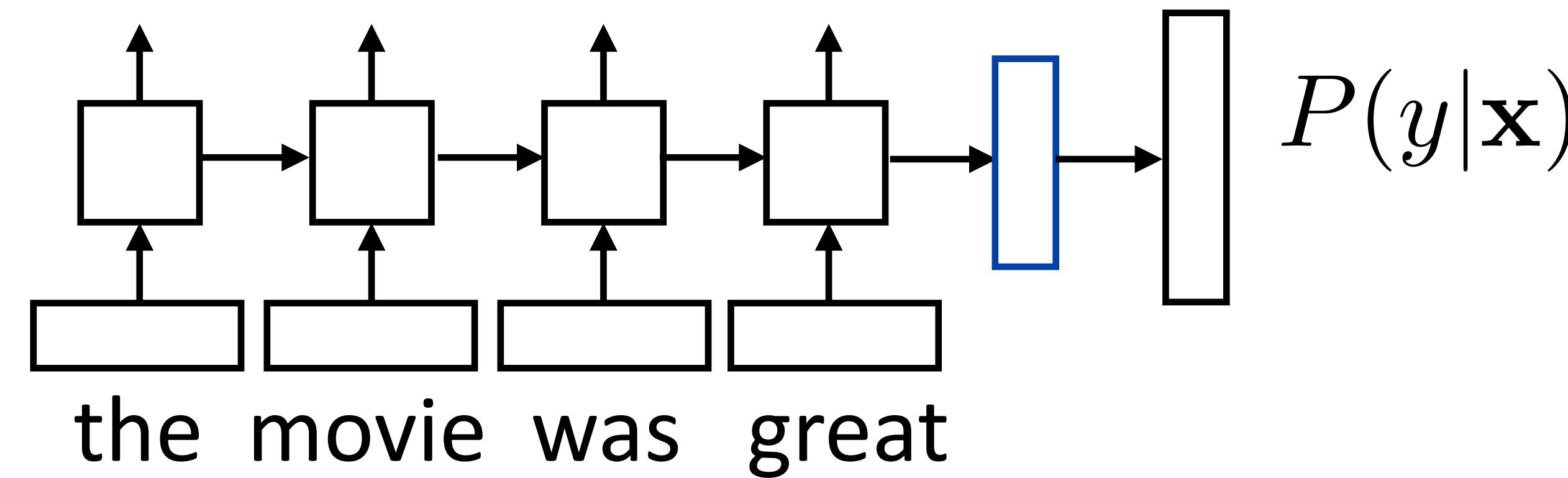
Training RNNs



Training RNNs

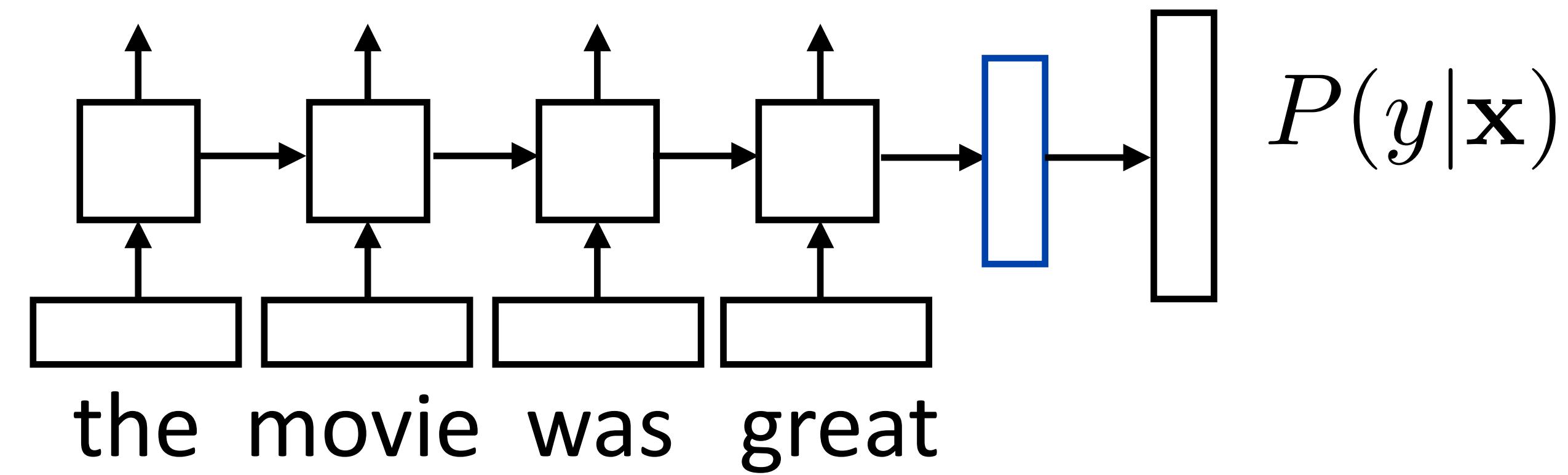


Training RNNs



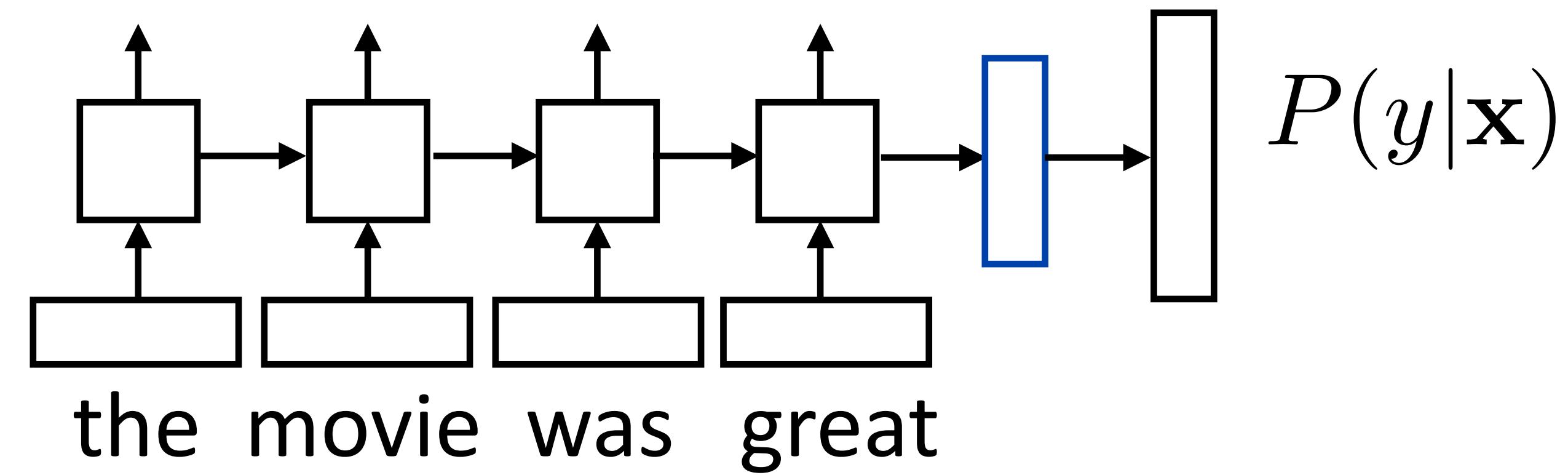
- ▶ Loss = negative log likelihood of probability of gold label (or use SVM or other loss)

Training RNNs



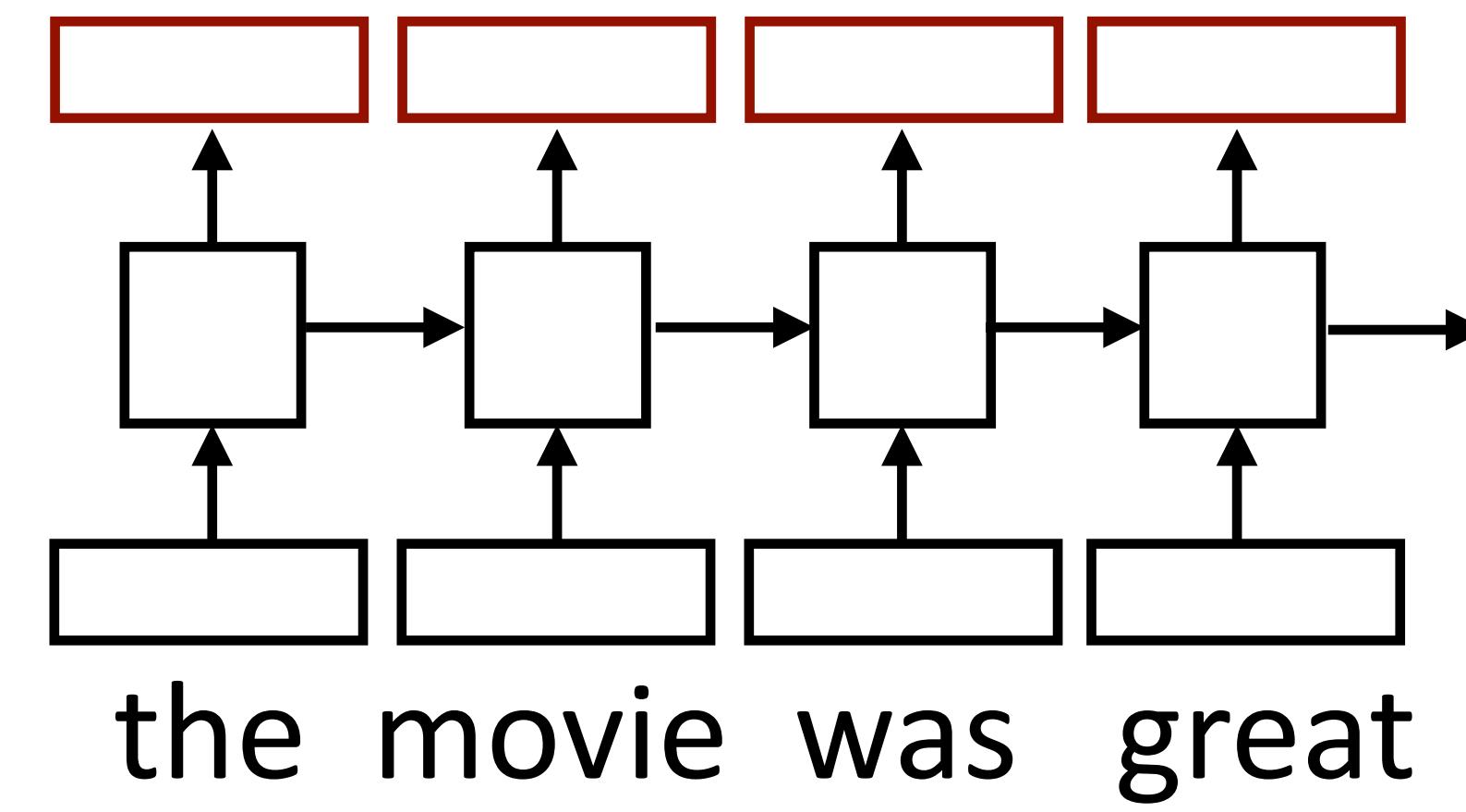
- ▶ Loss = negative log likelihood of probability of gold label (or use SVM or other loss)
- ▶ Backpropagate through entire network

Training RNNs

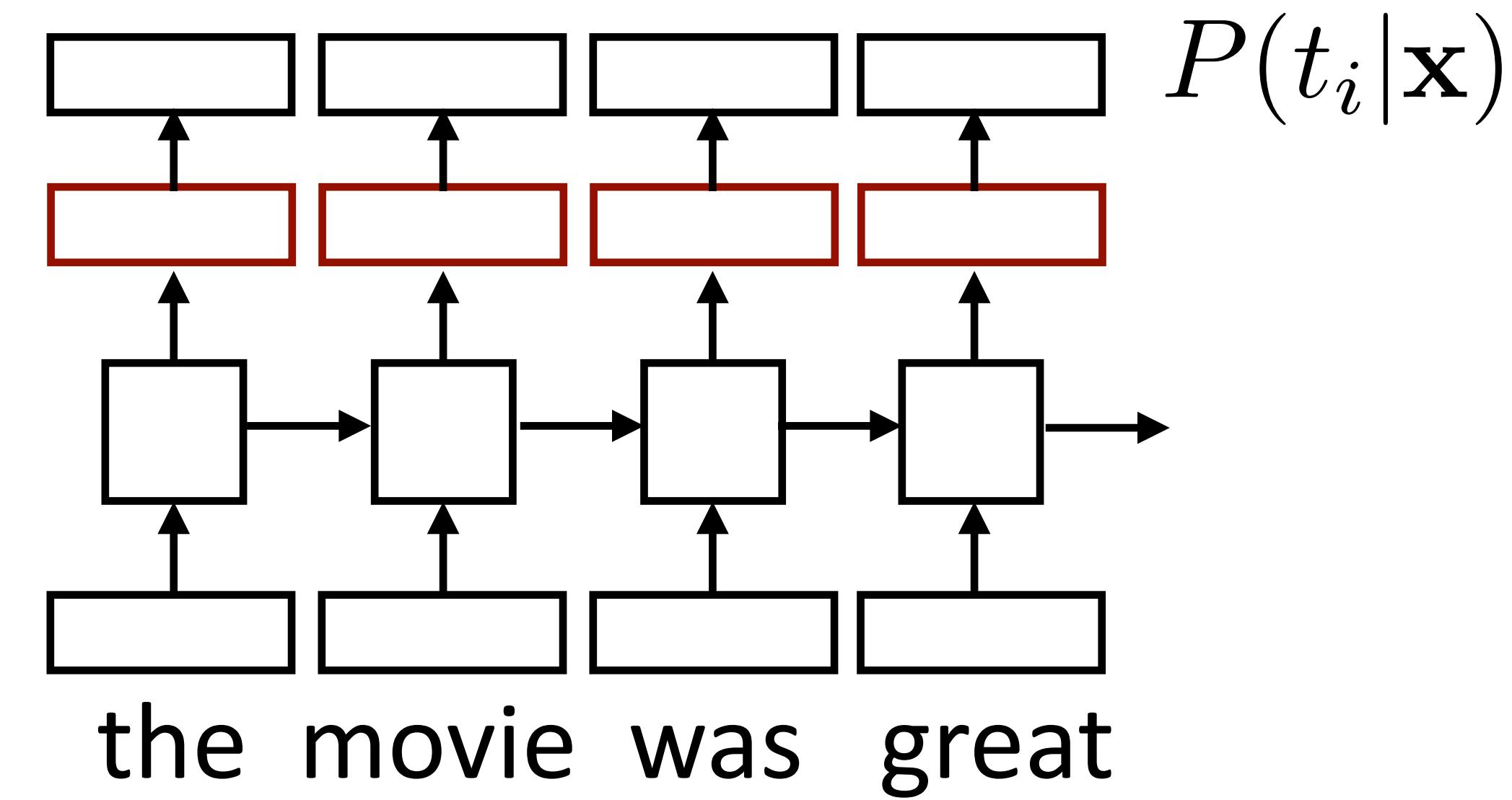


- ▶ Loss = negative log likelihood of probability of gold label (or use SVM or other loss)
- ▶ Backpropagate through entire network
- ▶ Example: sentiment analysis

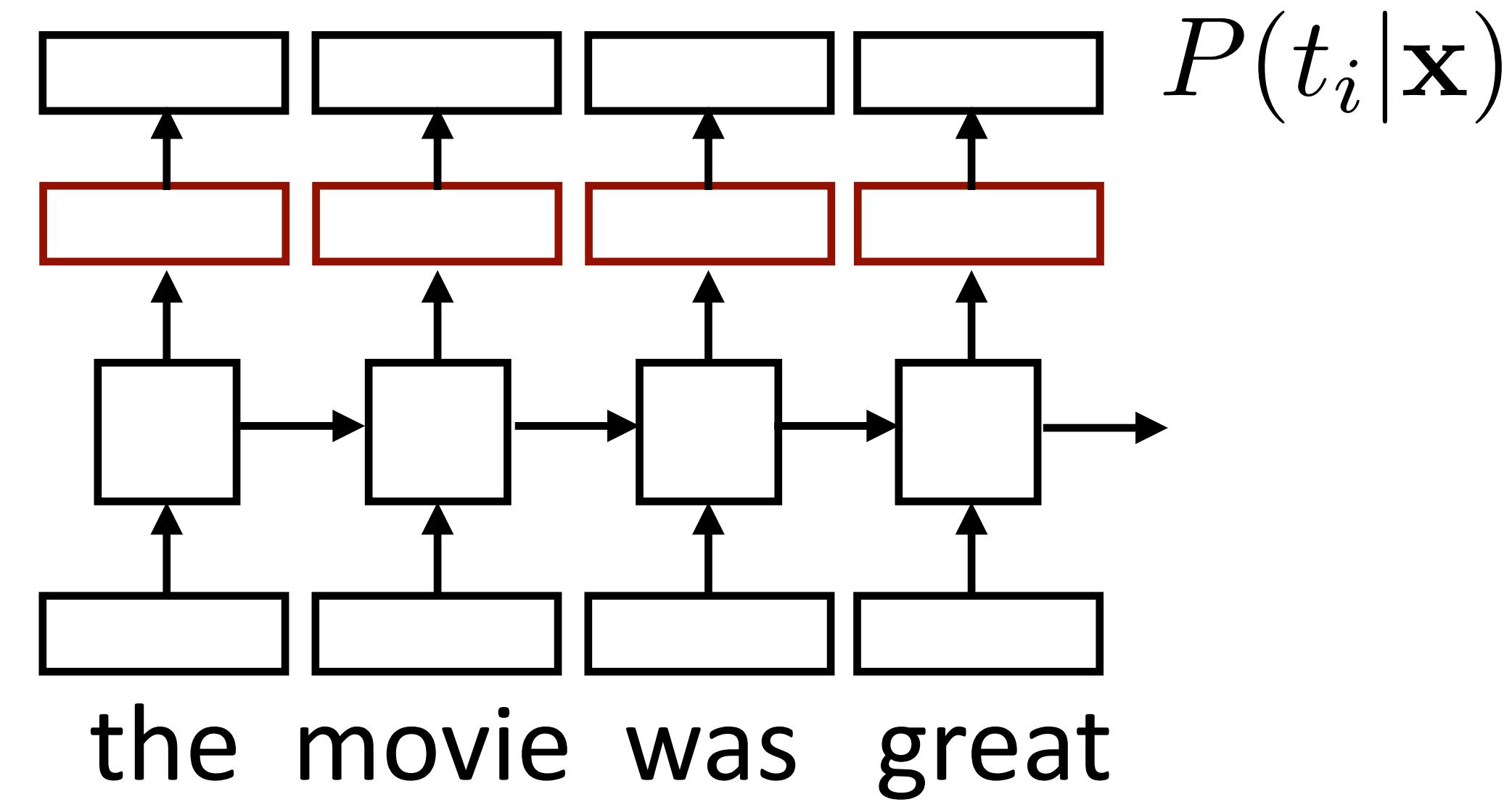
Training RNNs



Training RNNs

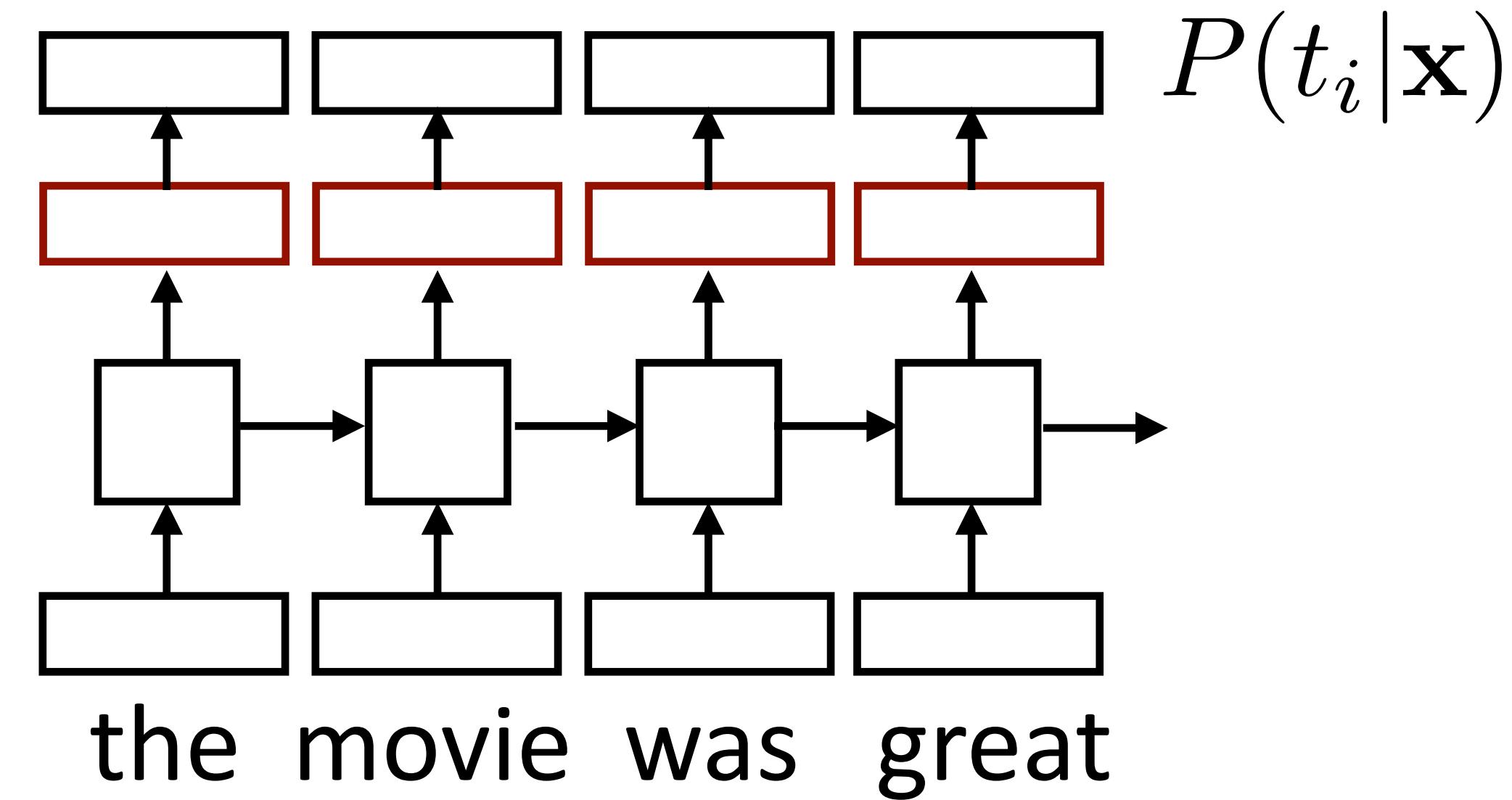


Training RNNs



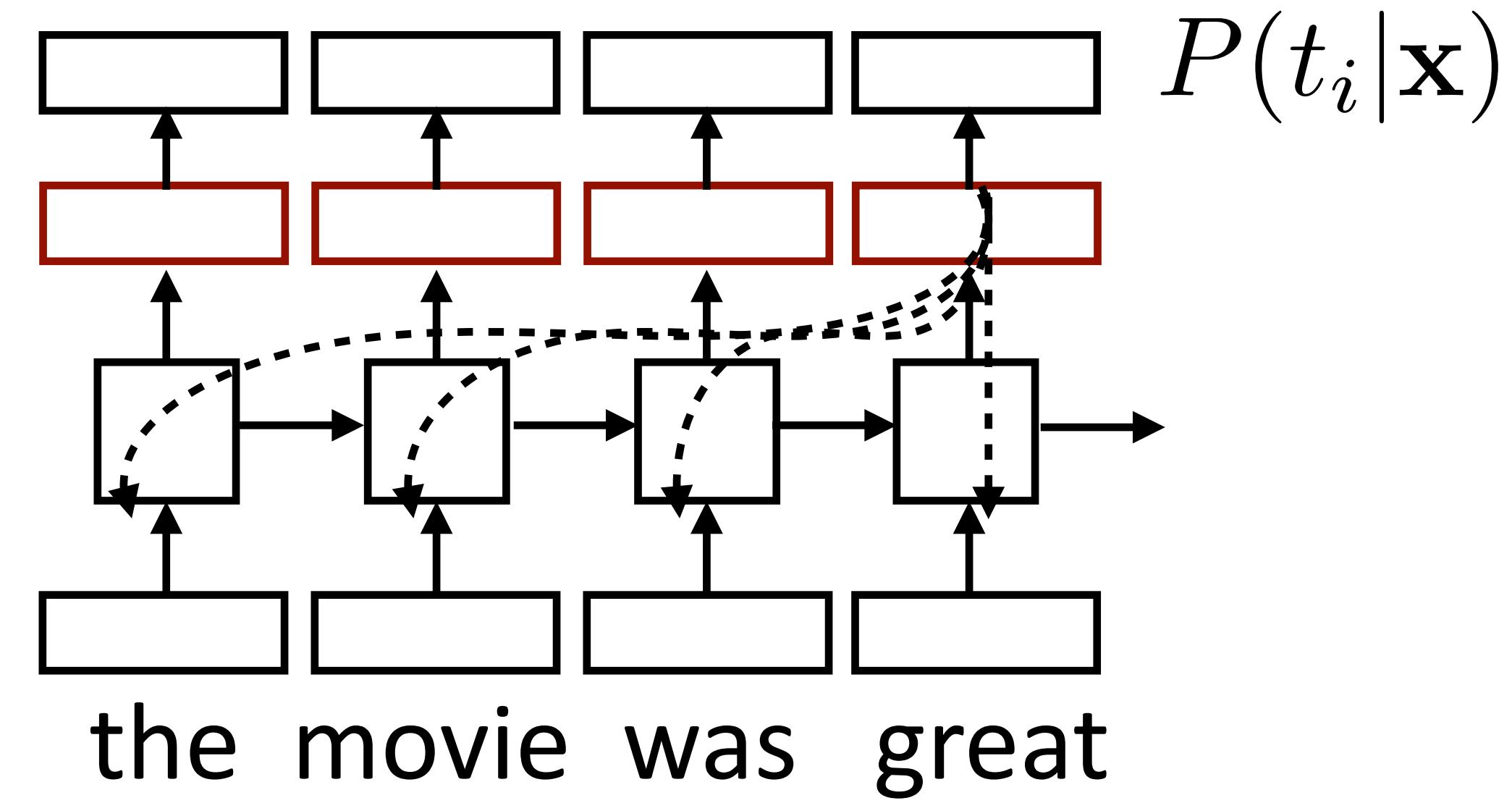
- ▶ Loss = negative log likelihood of probability of gold predictions, summed over the tags

Training RNNs



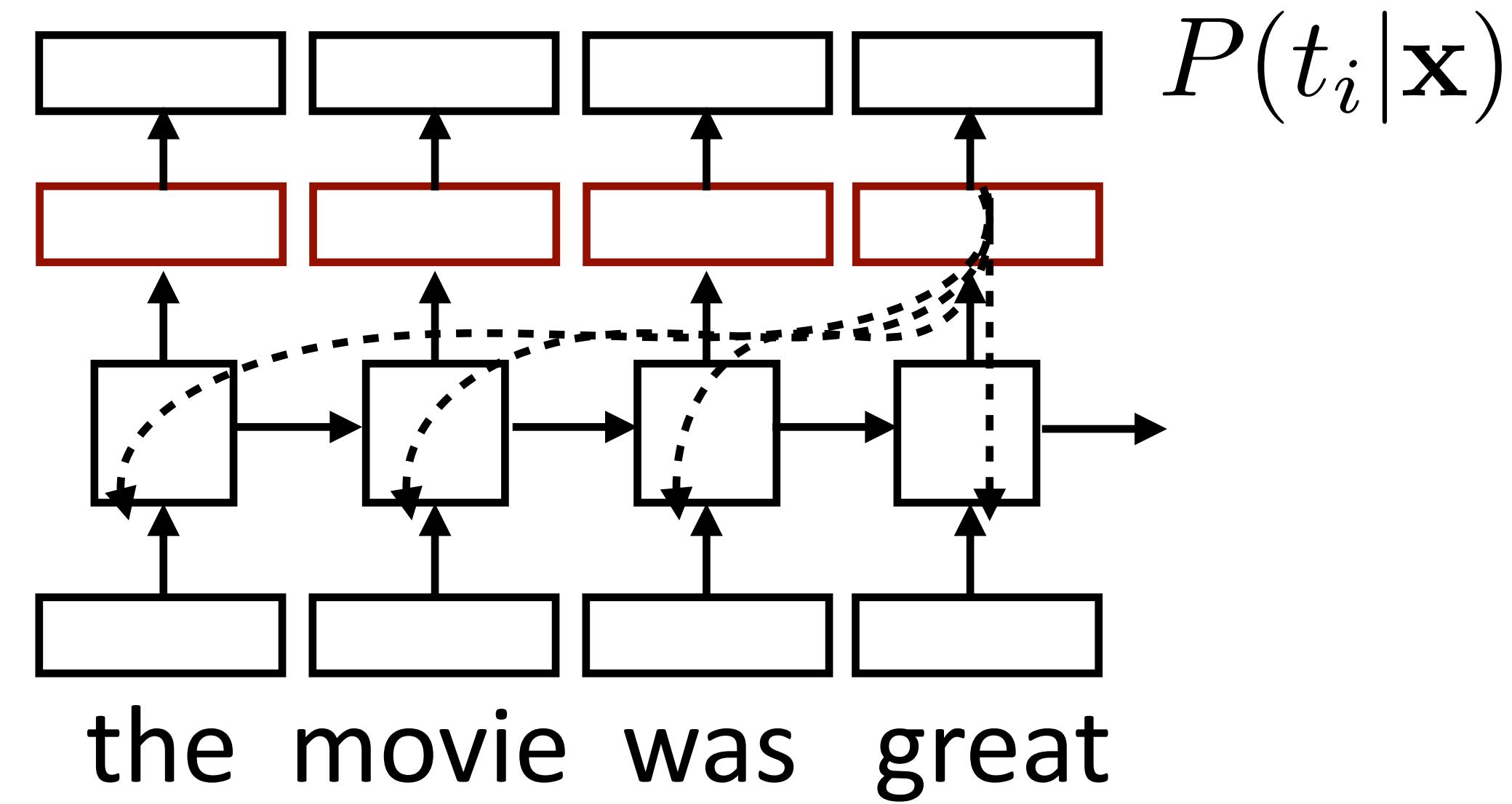
- ▶ Loss = negative log likelihood of probability of gold predictions, summed over the tags
- ▶ Loss terms filter back through network

Training RNNs



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Training RNNs



- ▶ Loss = negative log likelihood of probability of gold predictions, summed over the tags
- ▶ Loss terms filter back through network
- ▶ Example: language modeling (predict next word given context)

What can LSTMs model?

What can LSTMs model?

- ▶ Sentiment
 - ▶ Encode one sentence, predict
- ▶ Language models
 - ▶ Move left-to-right, per-token prediction

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- ▶ Translation
 - ▶ Encode sentence + then decode, use token predictions for attention weights

Visualizing LSTMs

Karpathy et al. (2015)

Visualizing LSTMs

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The sole importance of the crossing of the Berezina lies in the fact that it plainly and indubitably proved the fallacy of all the plans for cutting off the enemy's retreat and the soundness of the only possible line of action--the one Kutuzov and the general mass of the army demanded--namely, simply to follow the enemy up. The French crowd fled at a continually increasing speed and all its energy was directed to reaching its goal. It fled like a wounded animal and it was impossible to block its path. This was shown not so much by the arrangements it made for crossing as by what took place at the bridges. When the bridges broke down, unarmed soldiers, people from Moscow and women with children who were with the French transport, all--carried on by vis inertiae--pressed forward into boats and into the ice-covered water and did not, surrender.

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"You mean to imply that I have nothing to eat out of.... on the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."

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- ▶ Binary switch: tells us if we're in a quote or not

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#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
    int i;
    if (classes[class]) {
        for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
            if (mask[i] & classes[class][i])
                return 0;
    }
    return 1;
}
```

Visualizing LSTMs

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- ▶ Visualize activations of specific cells to see what they track
- ▶ Stack: activation based on indentation

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```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
    char *str;
    if (!*bufp || (len == 0) || (len > *remain))
        return ERR_PTR(-EINVAL);
    /* of the currently implemented string fields, PATH_MAX
     * defines the longest valid length.
    */
```

Visualizing LSTMs

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- ▶ Visualize activations of specific cells to see what they track
- ▶ Uninterpretable: probably doing double-duty, or only makes sense in the context of another activation

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CNNs vs. LSTMs

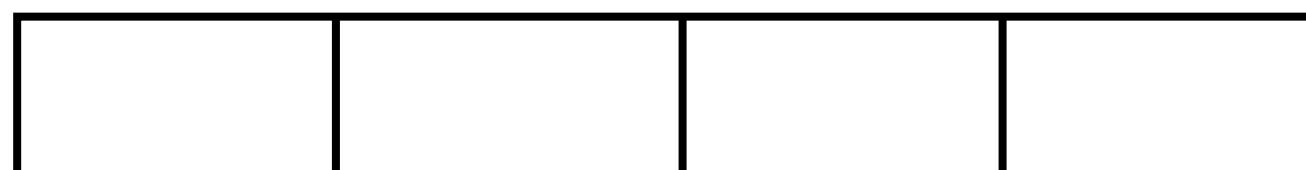


the movie was good

CNNs vs. LSTMs



c filters,
 $m \times k$ each



$n \times k$

the movie was good

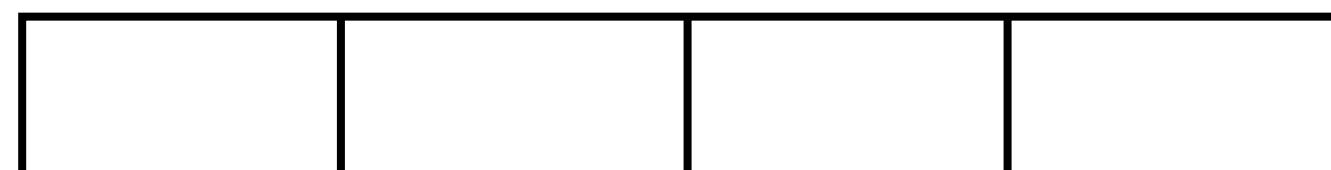
CNNs vs. LSTMs



$O(n) \times c$



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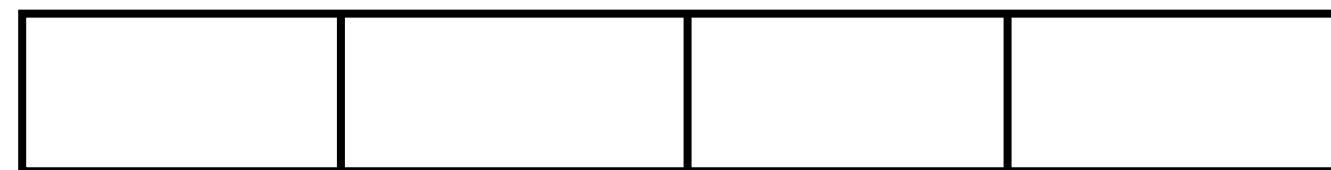
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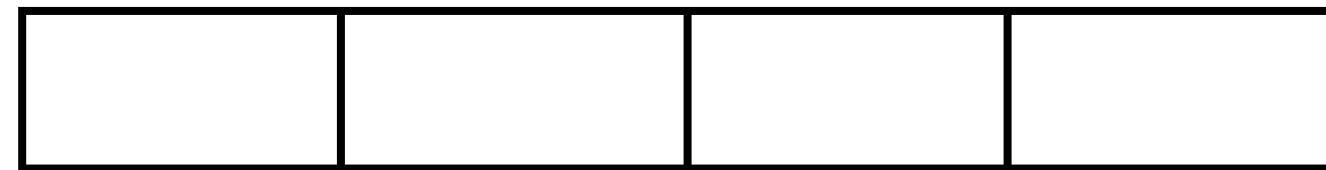
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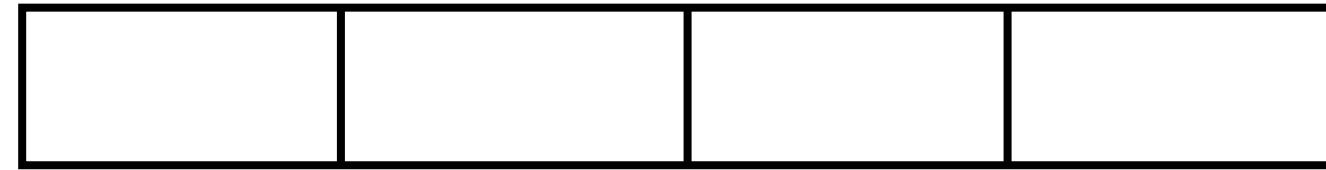
CNNs vs. LSTMs



$O(n) \times c$

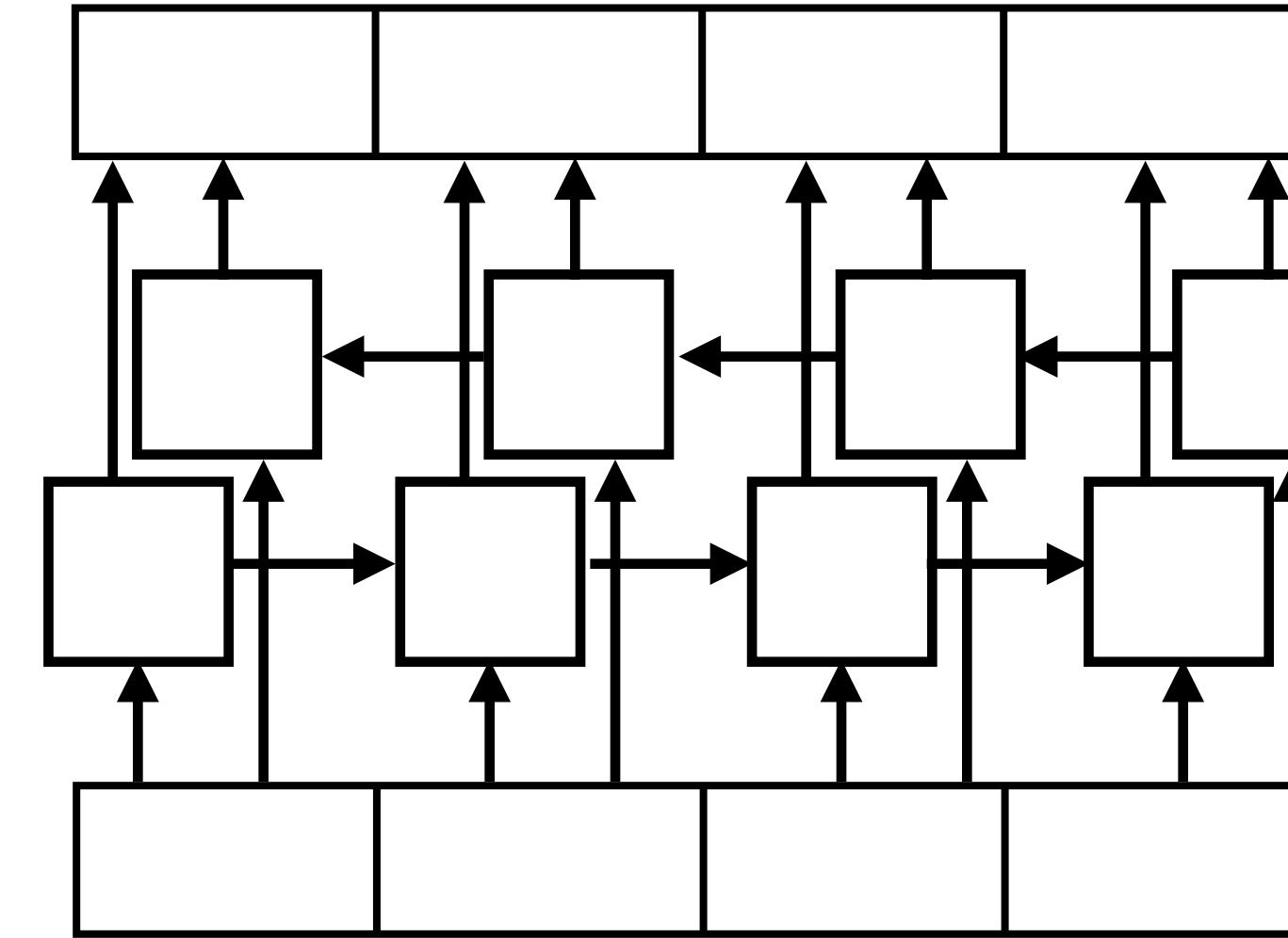


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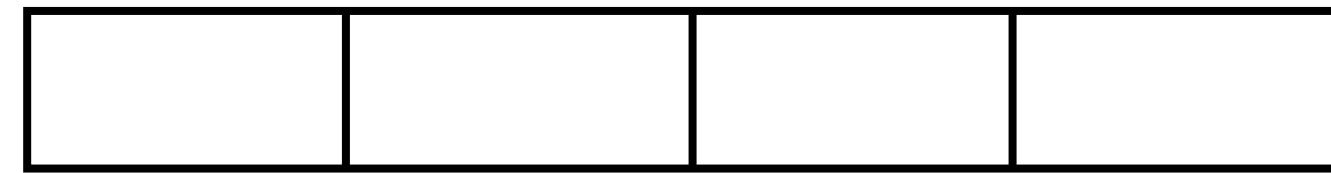
$n \times 2c$

BiLSTM with
hidden size c

$n \times k$

the movie was good

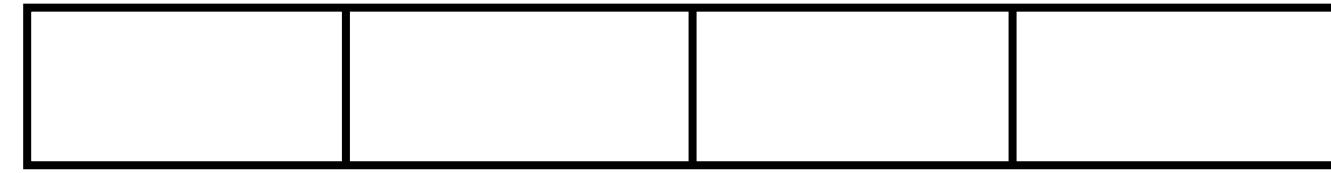
CNNs vs. LSTMs



$O(n) \times c$

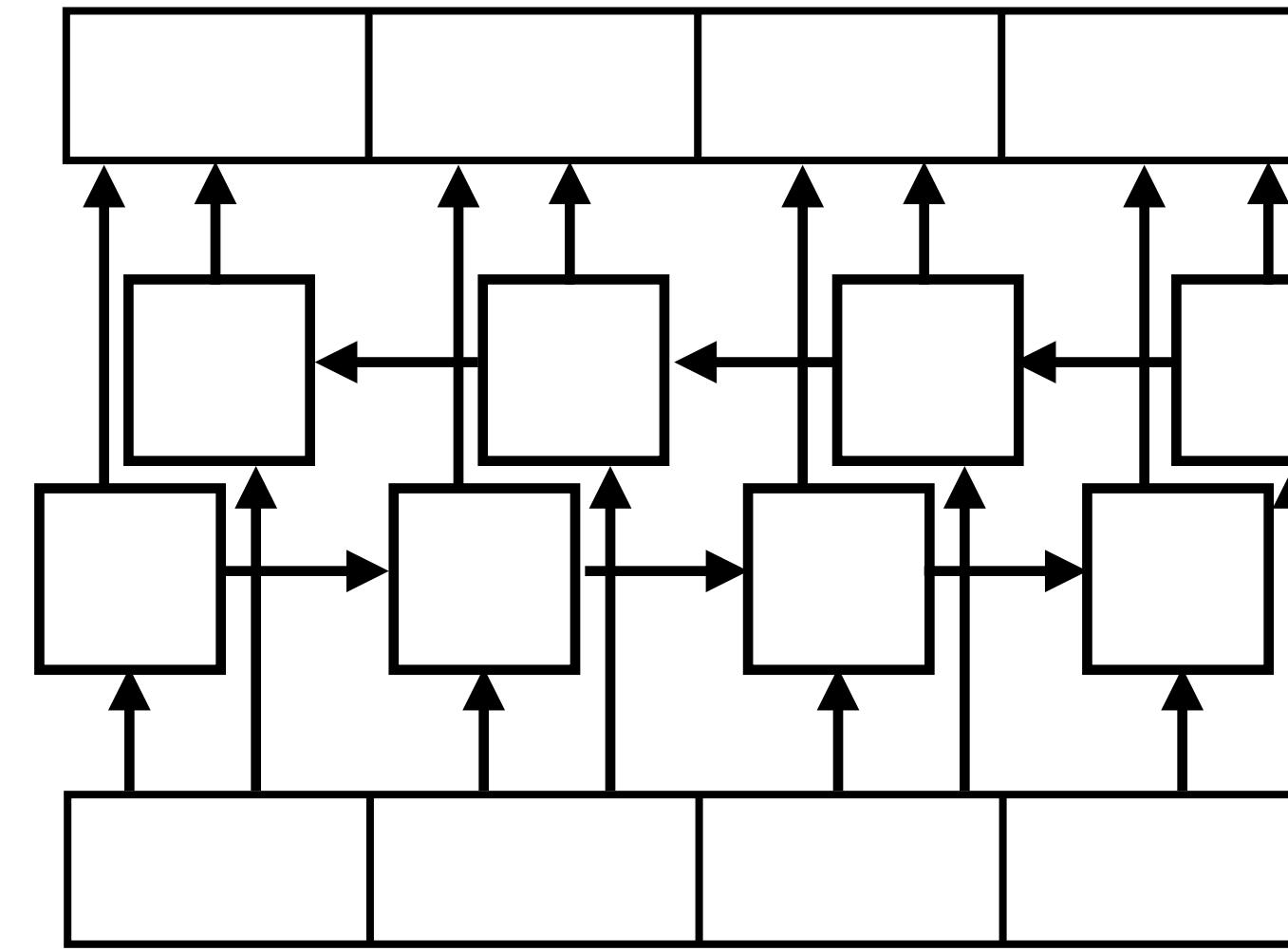


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the movie was good



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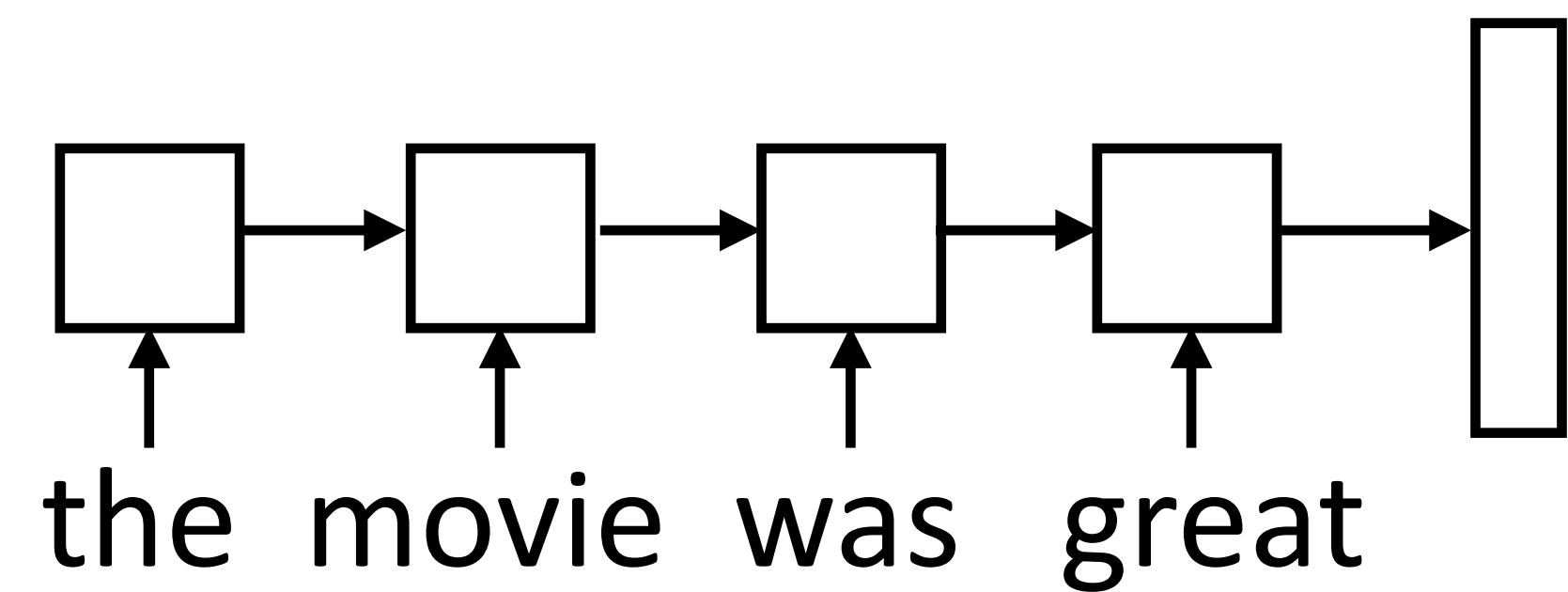
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- ▶ Both LSTMs and convolutional layers transform the input using context
- ▶ LSTM: “globally” looks at the entire sentence (but local for many problems)
- ▶ CNN: local depending on filter width + number of layers

Text-to-Text Generation

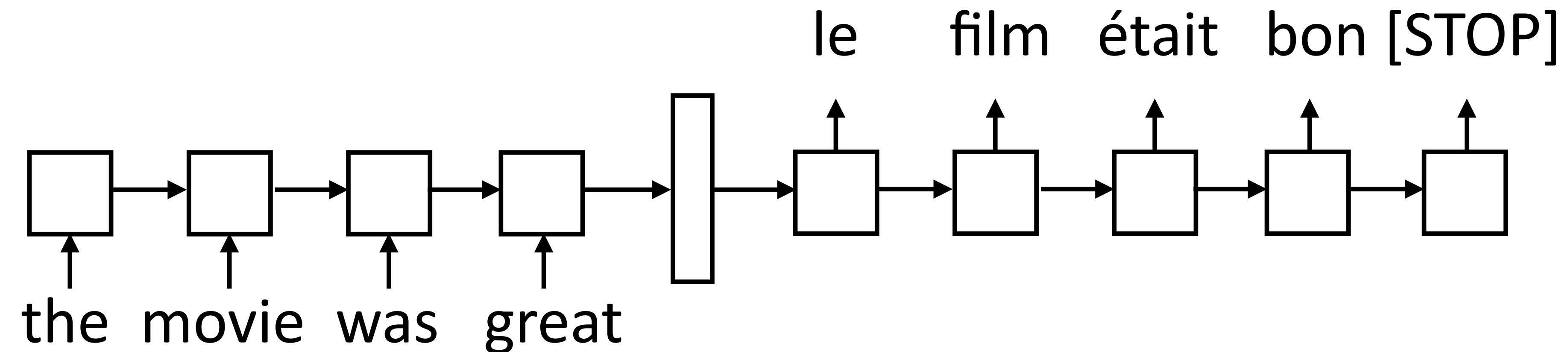
Encoder-Decoder

- ▶ Encode a sequence into a fixed-sized vector



Encoder-Decoder

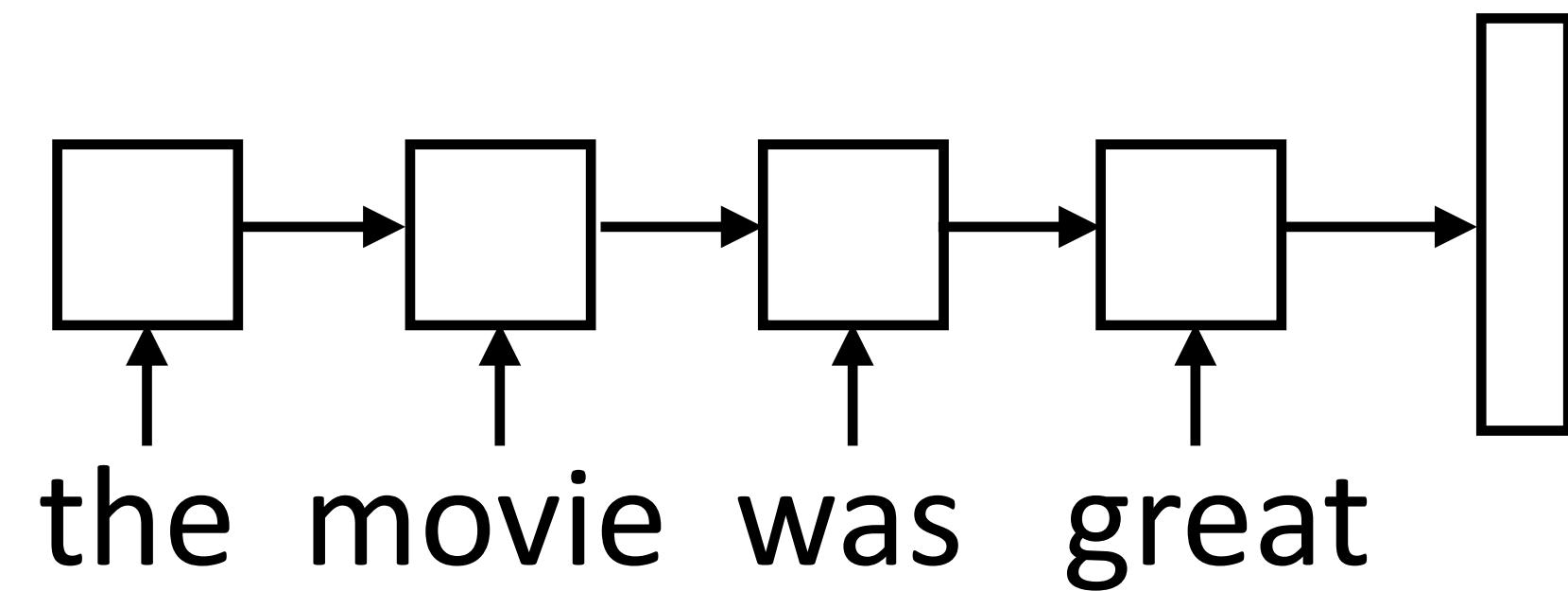
- ▶ Encode a sequence into a fixed-sized vector



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

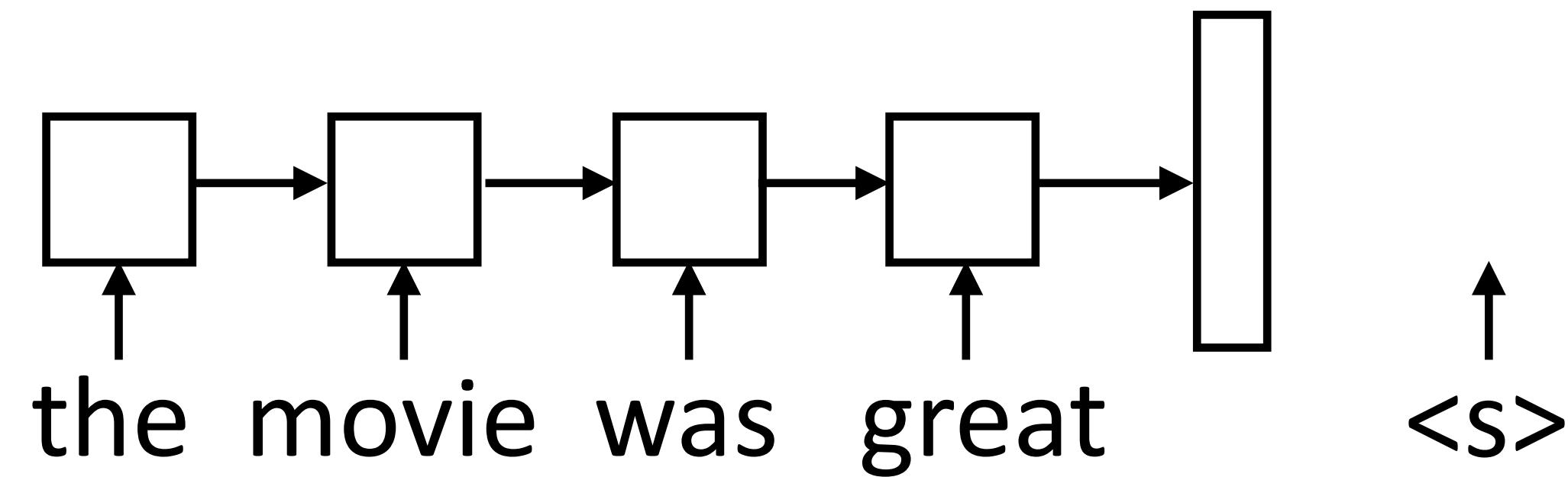
Model

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



Model

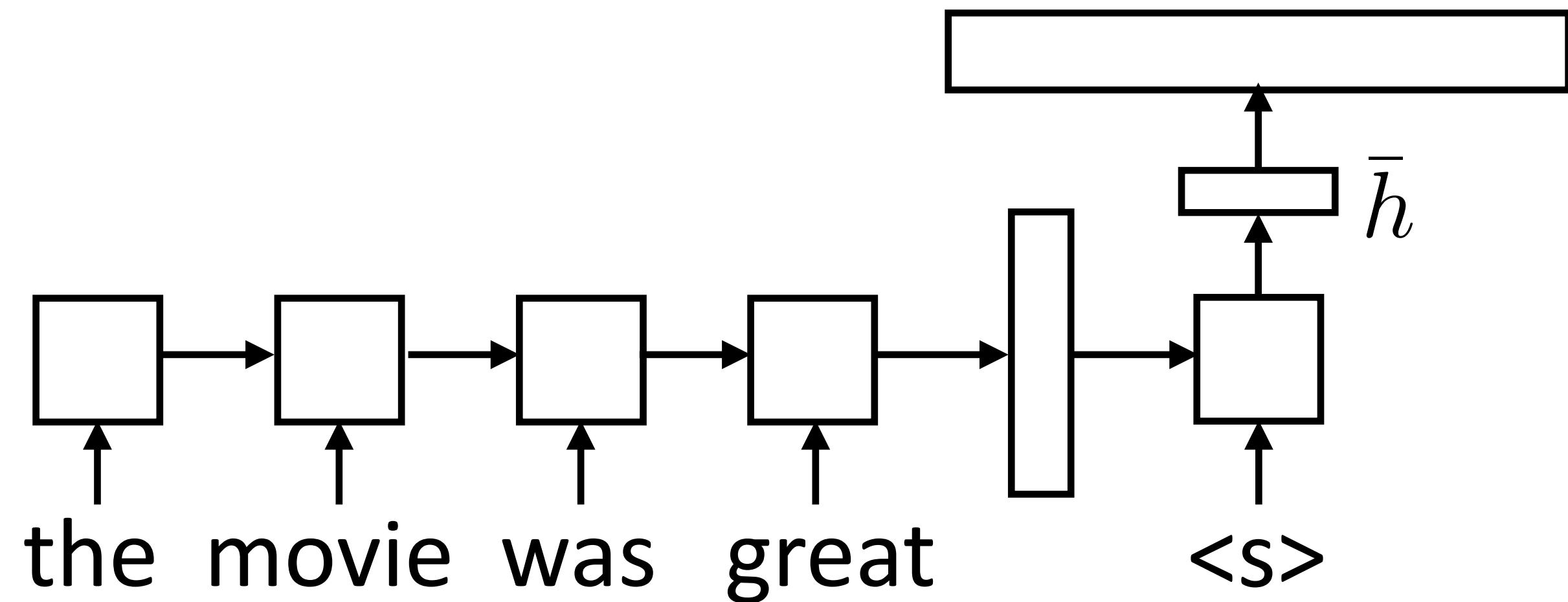
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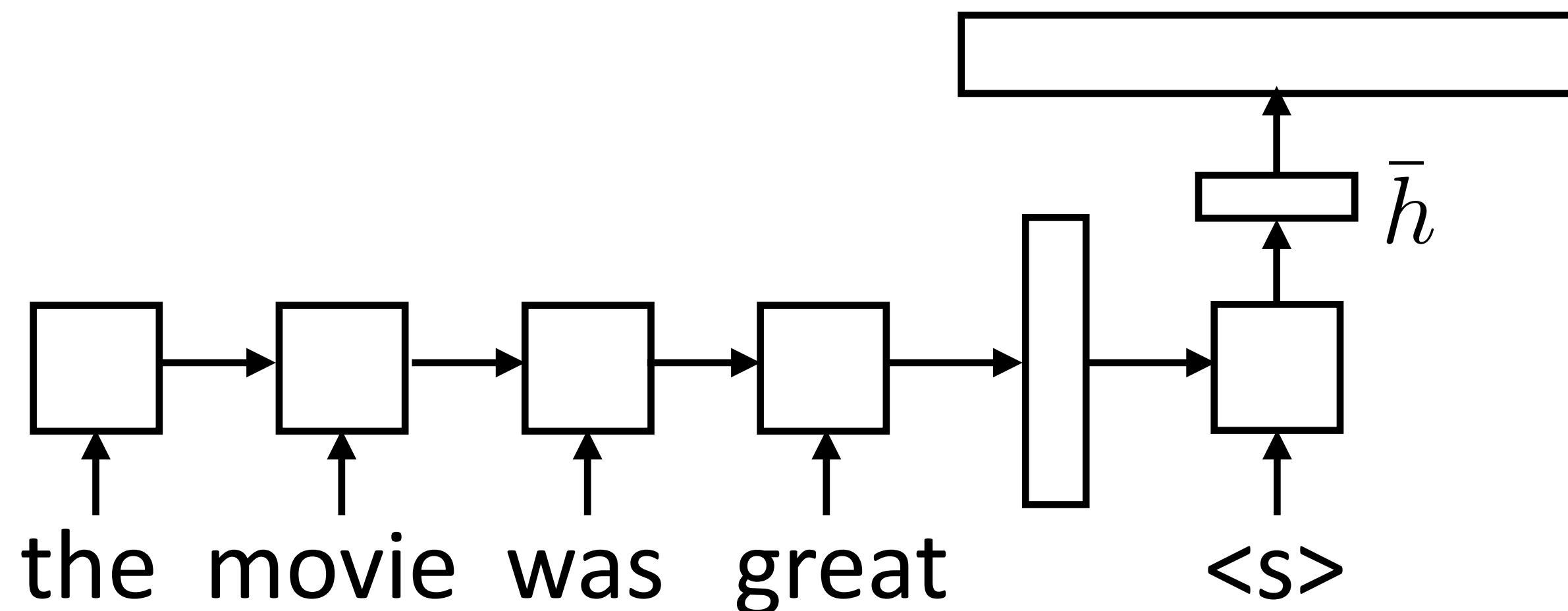
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- ▶ W size is $|\text{vocab}| \times |\text{hidden state}|$, softmax over entire vocabulary

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



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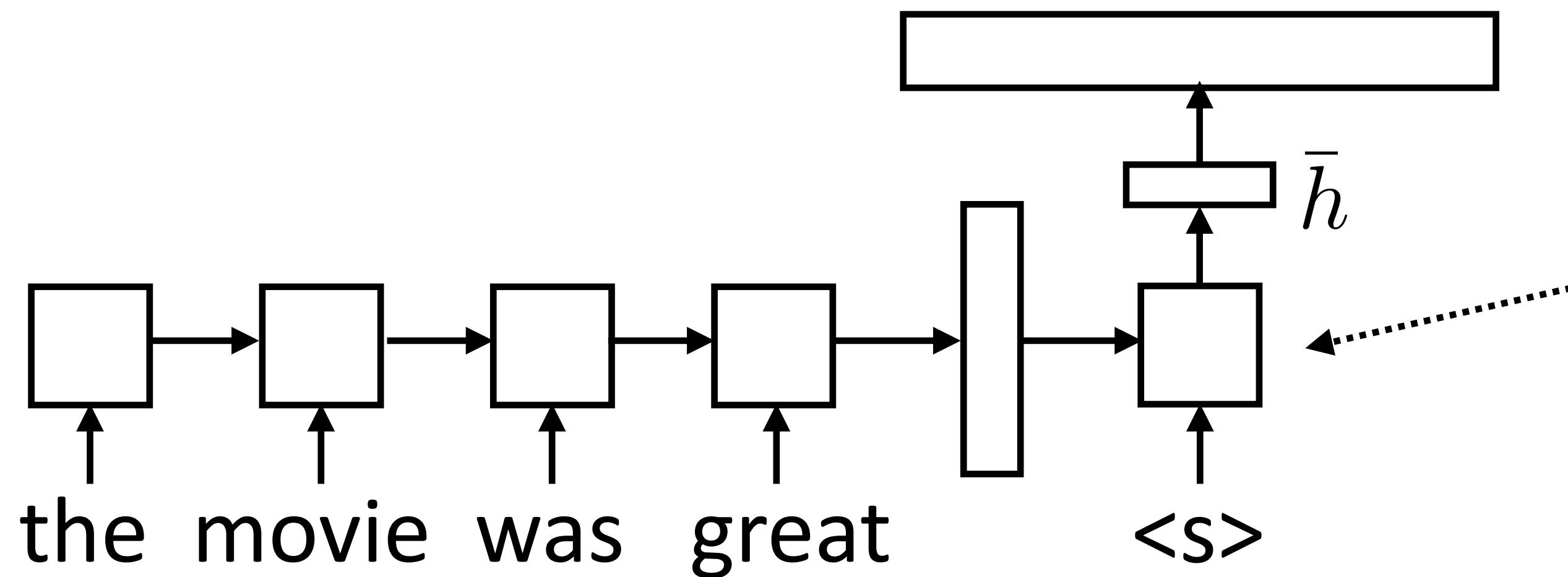


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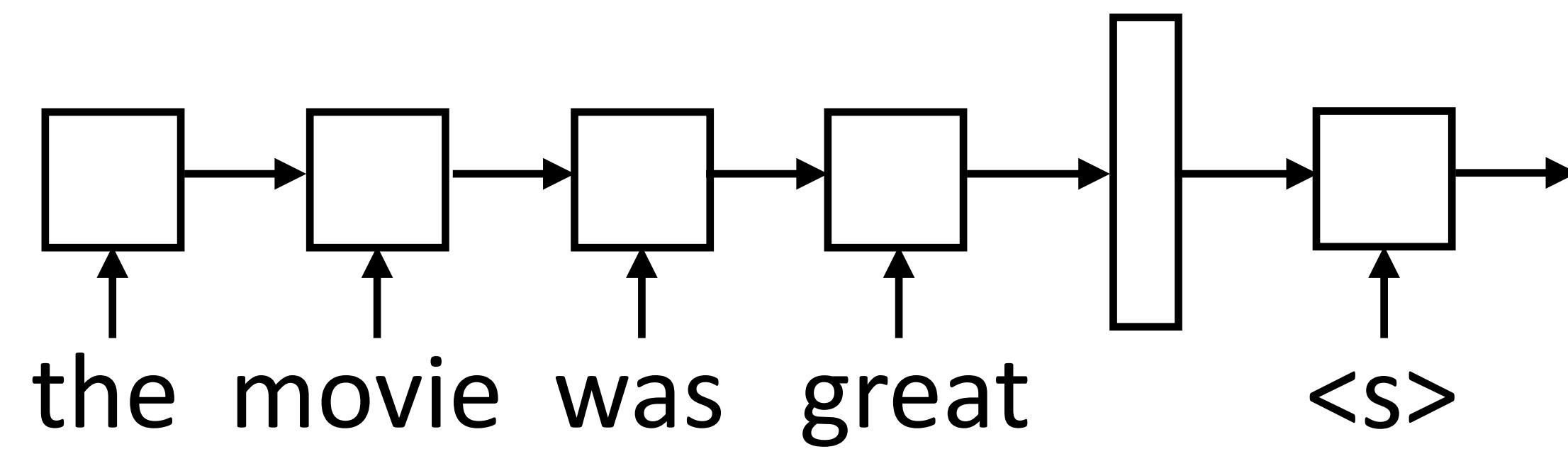
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Decoder has separate parameters from encoder, so this can learn to be a language model (produce a plausible next word given current one)

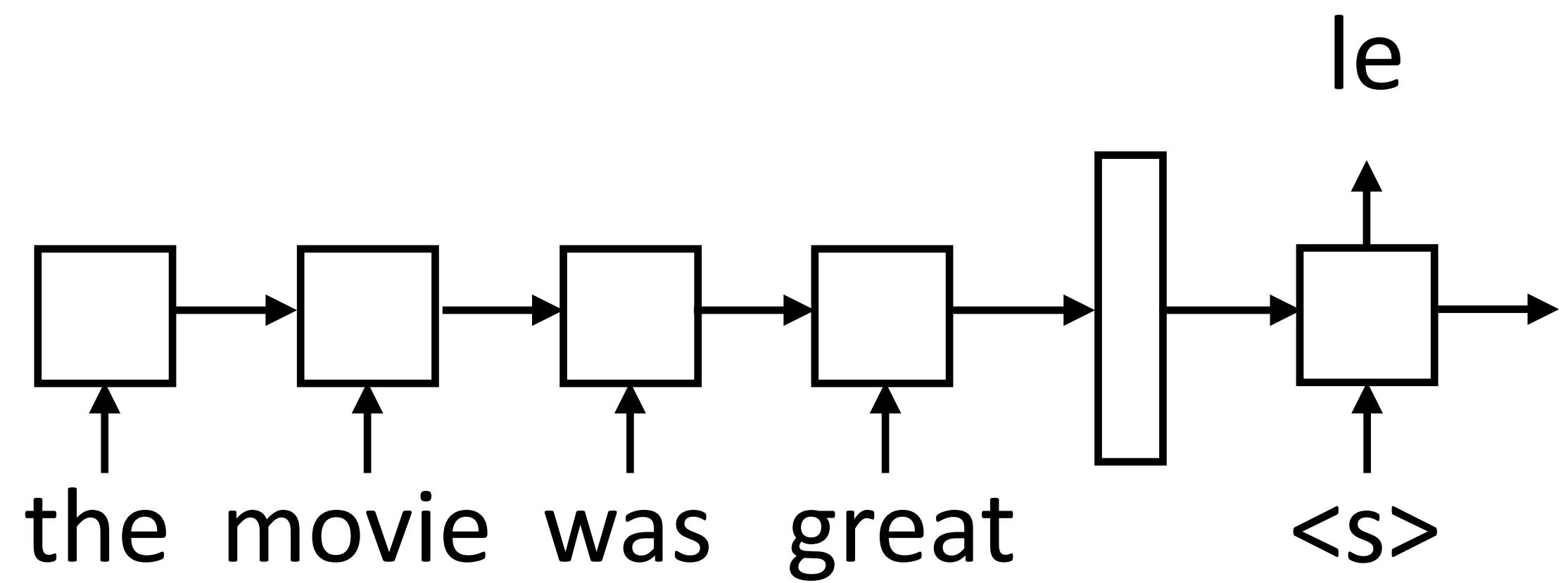
Inference

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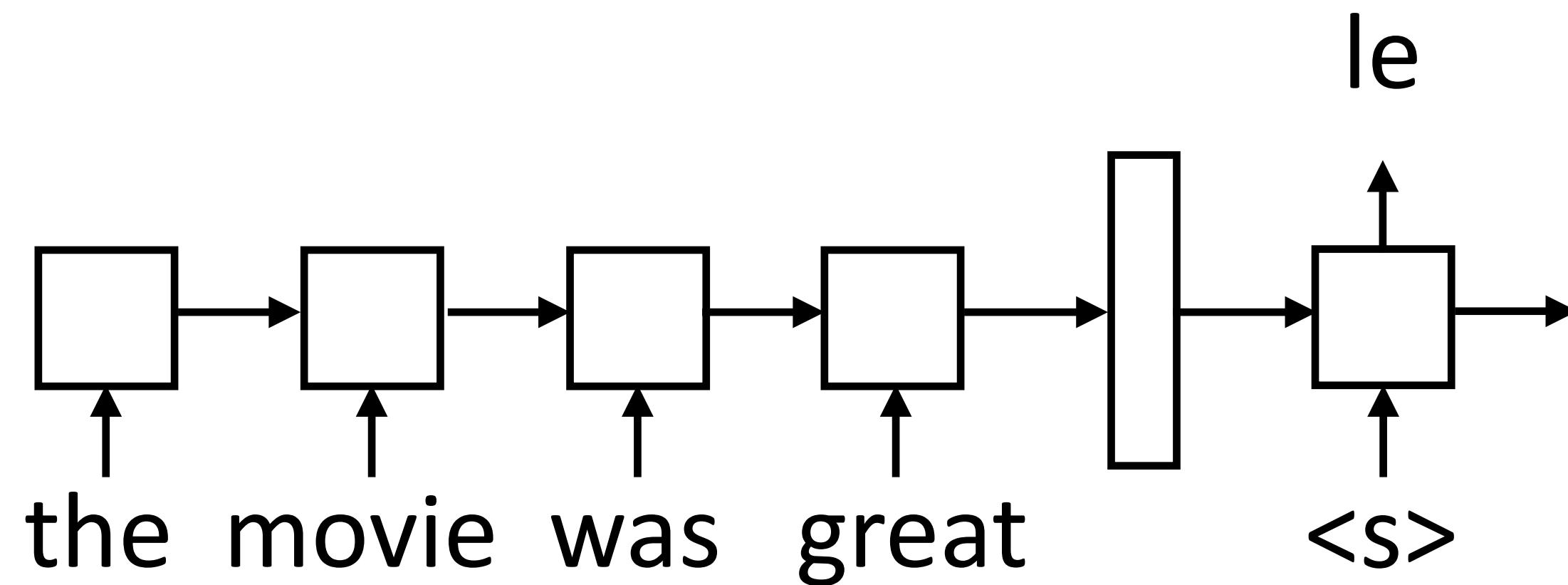
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Inference

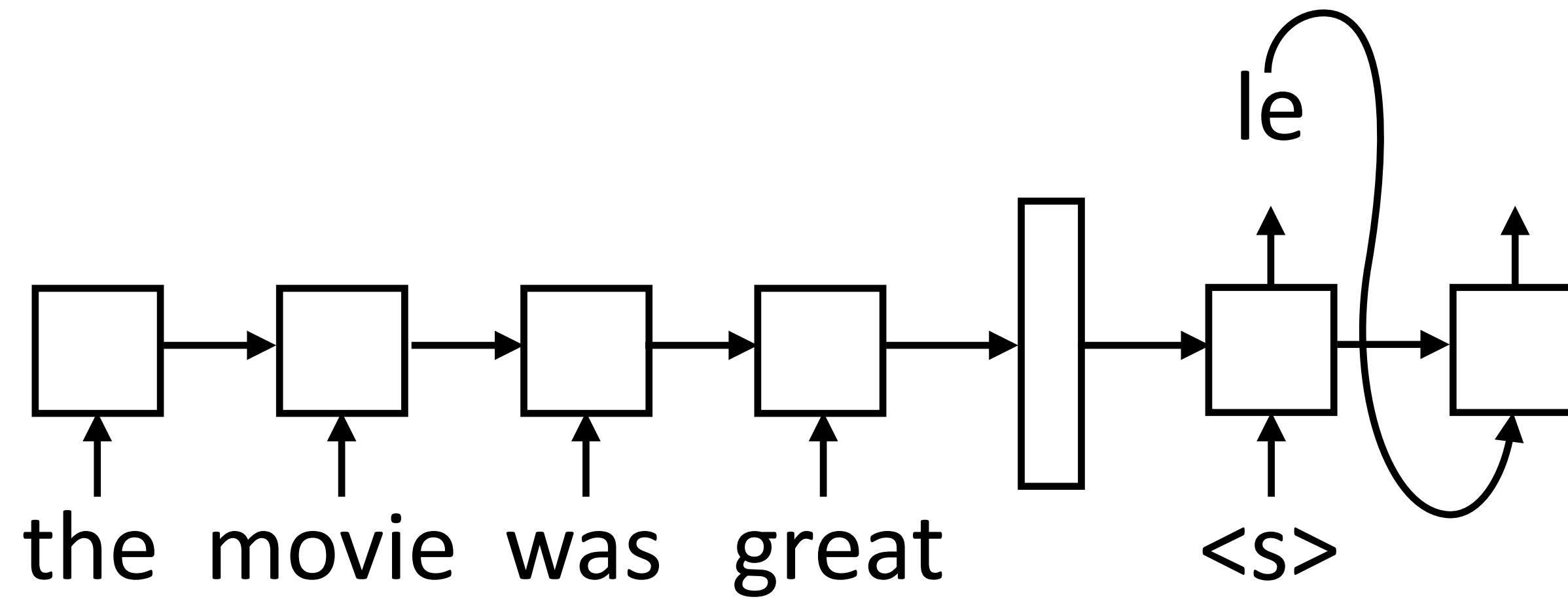
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- ▶ During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state

Inference

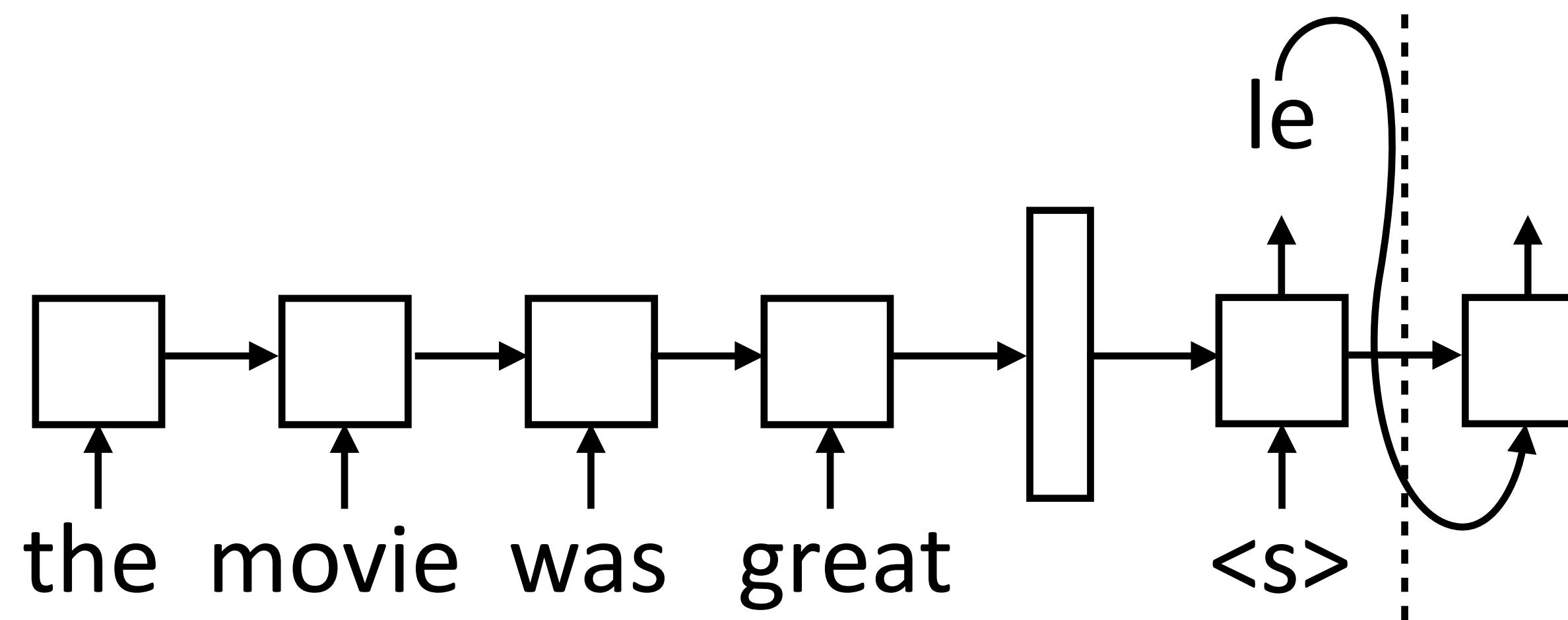
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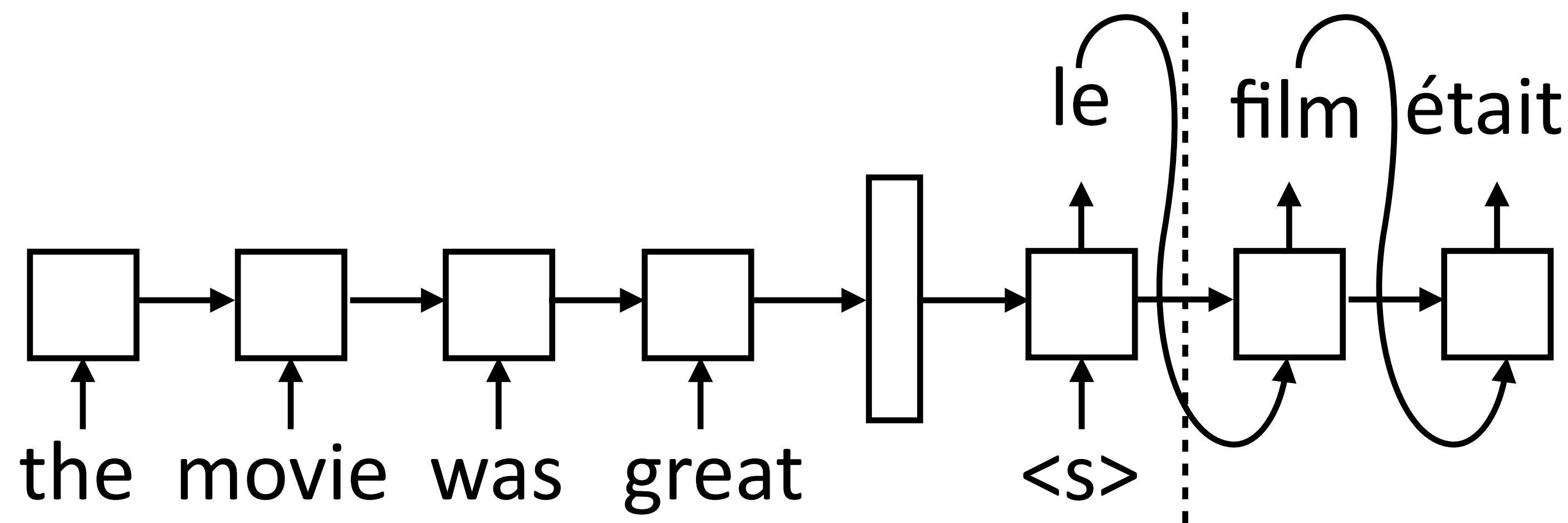
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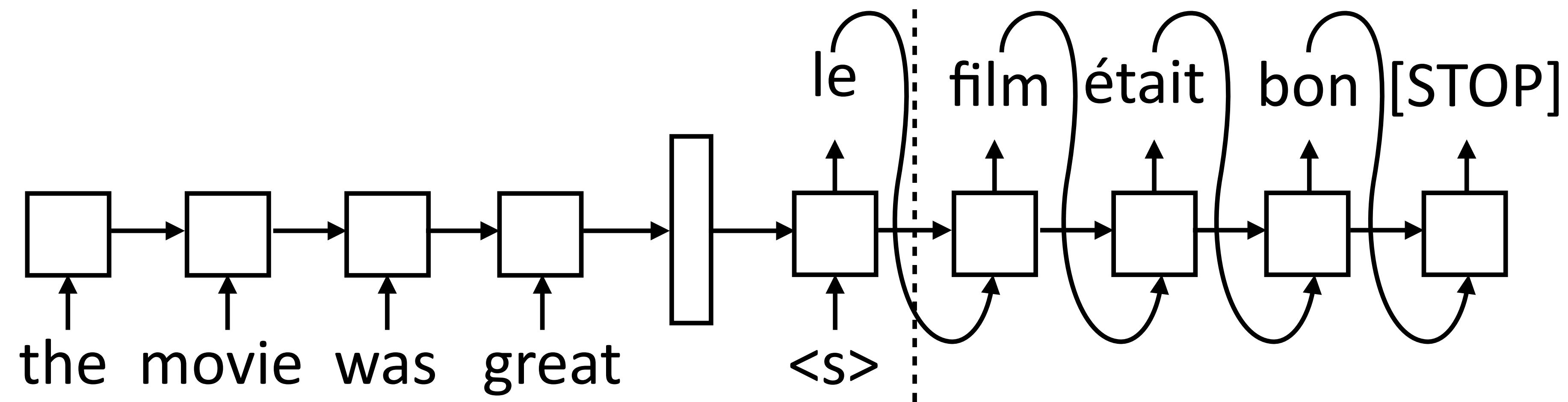
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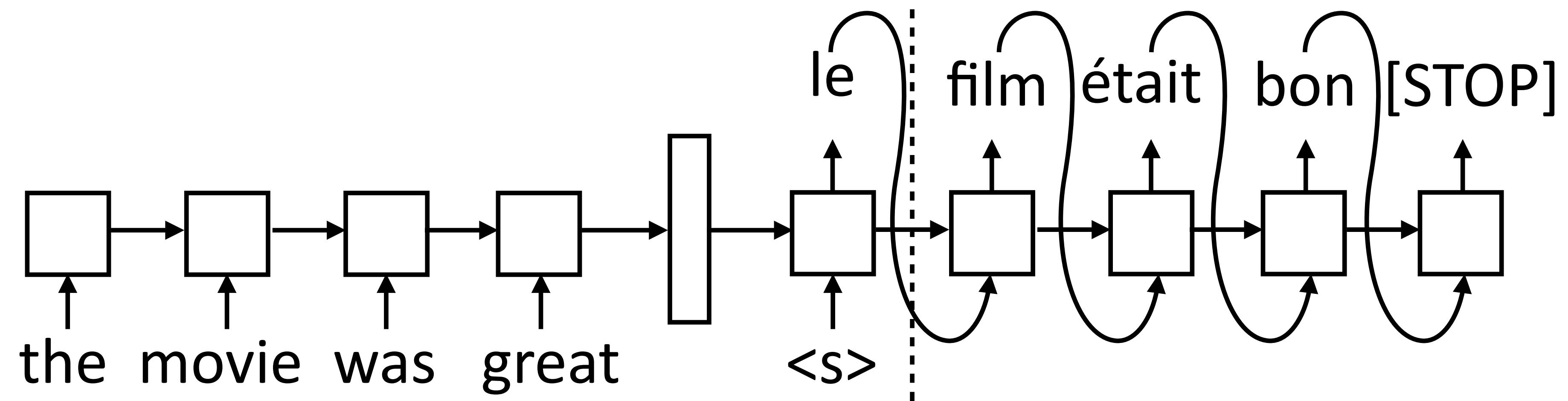
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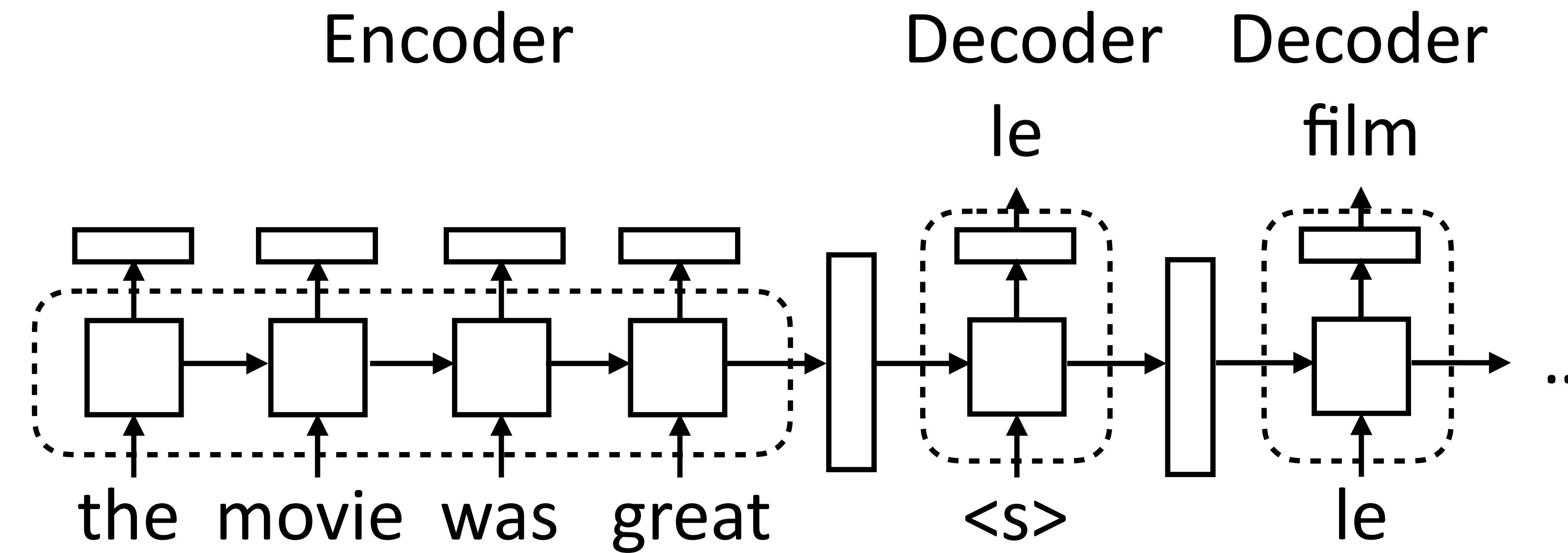
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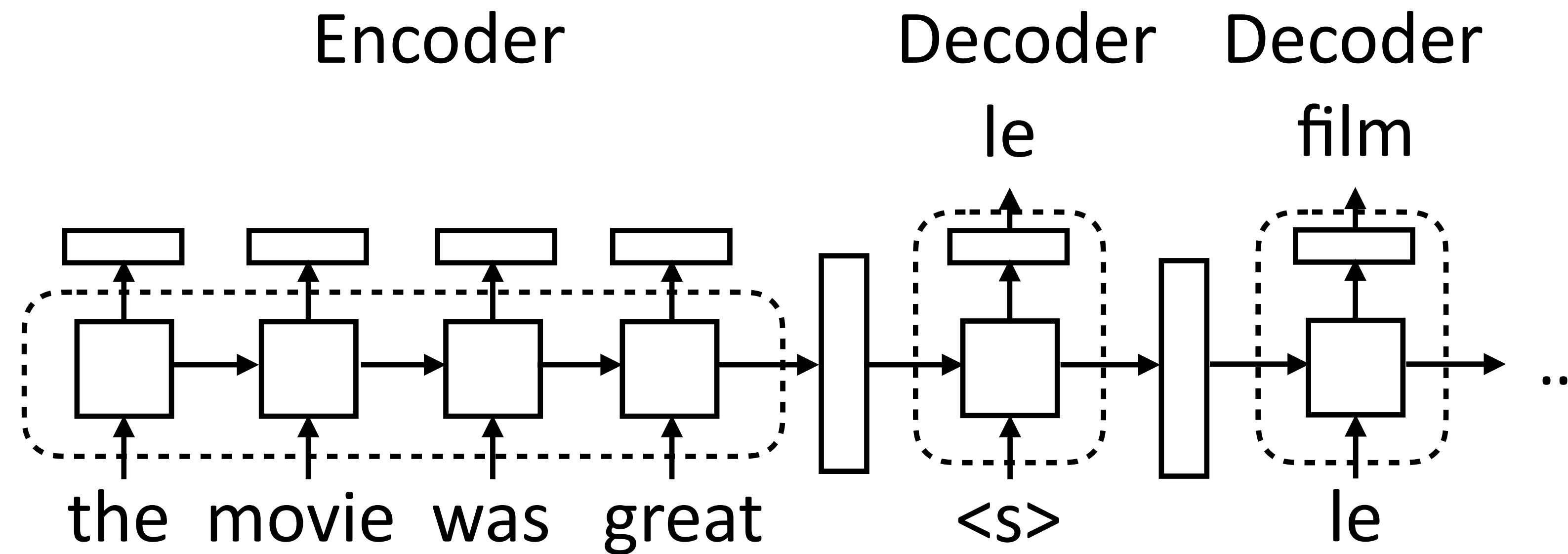


- ▶ During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- ▶ Need to actually evaluate computation graph up to this point to form input for the next state
- ▶ Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models

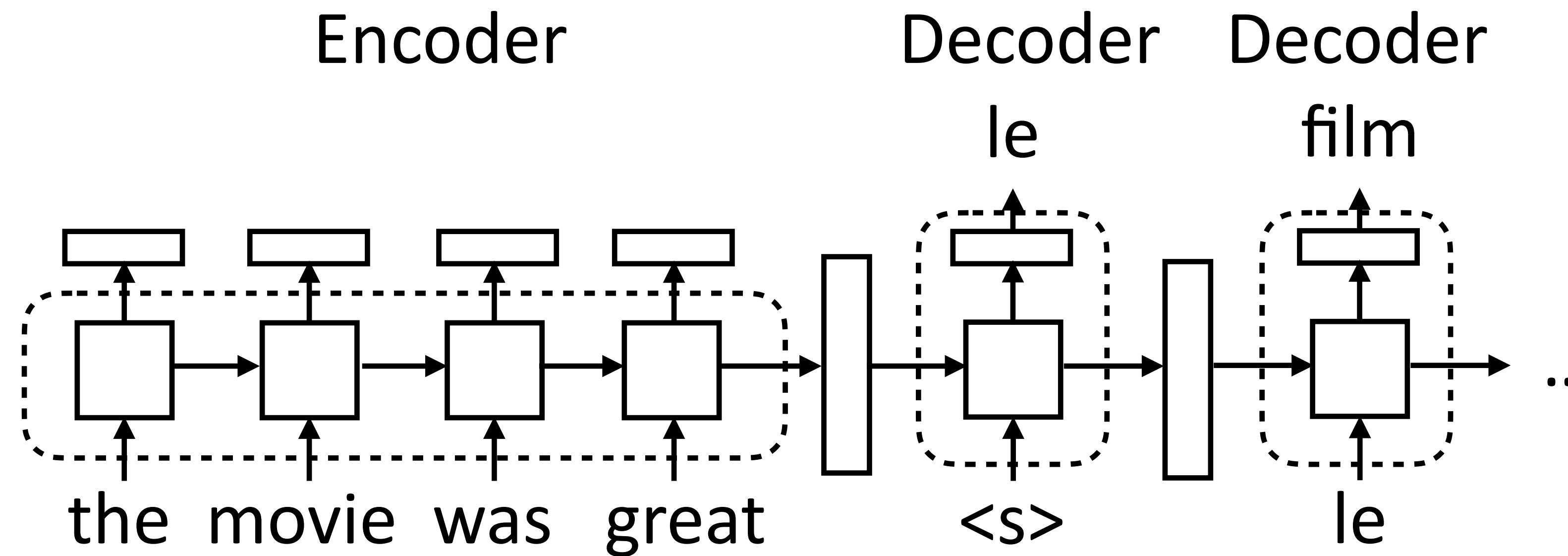


Implementing seq2seq Models



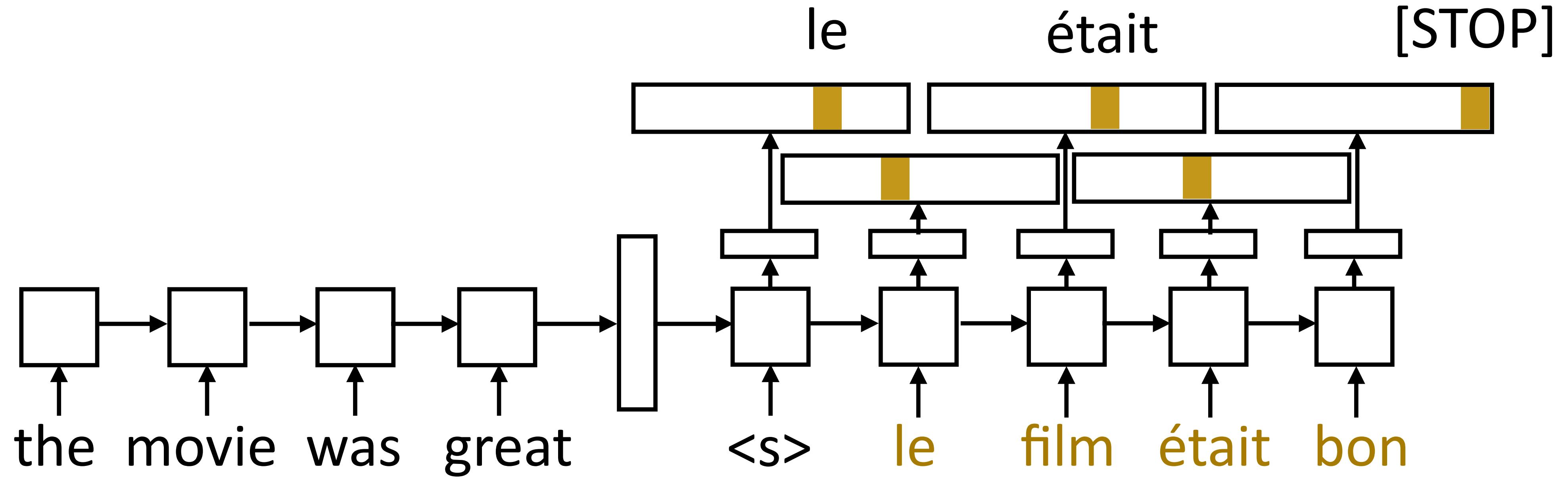
- ▶ Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks

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

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

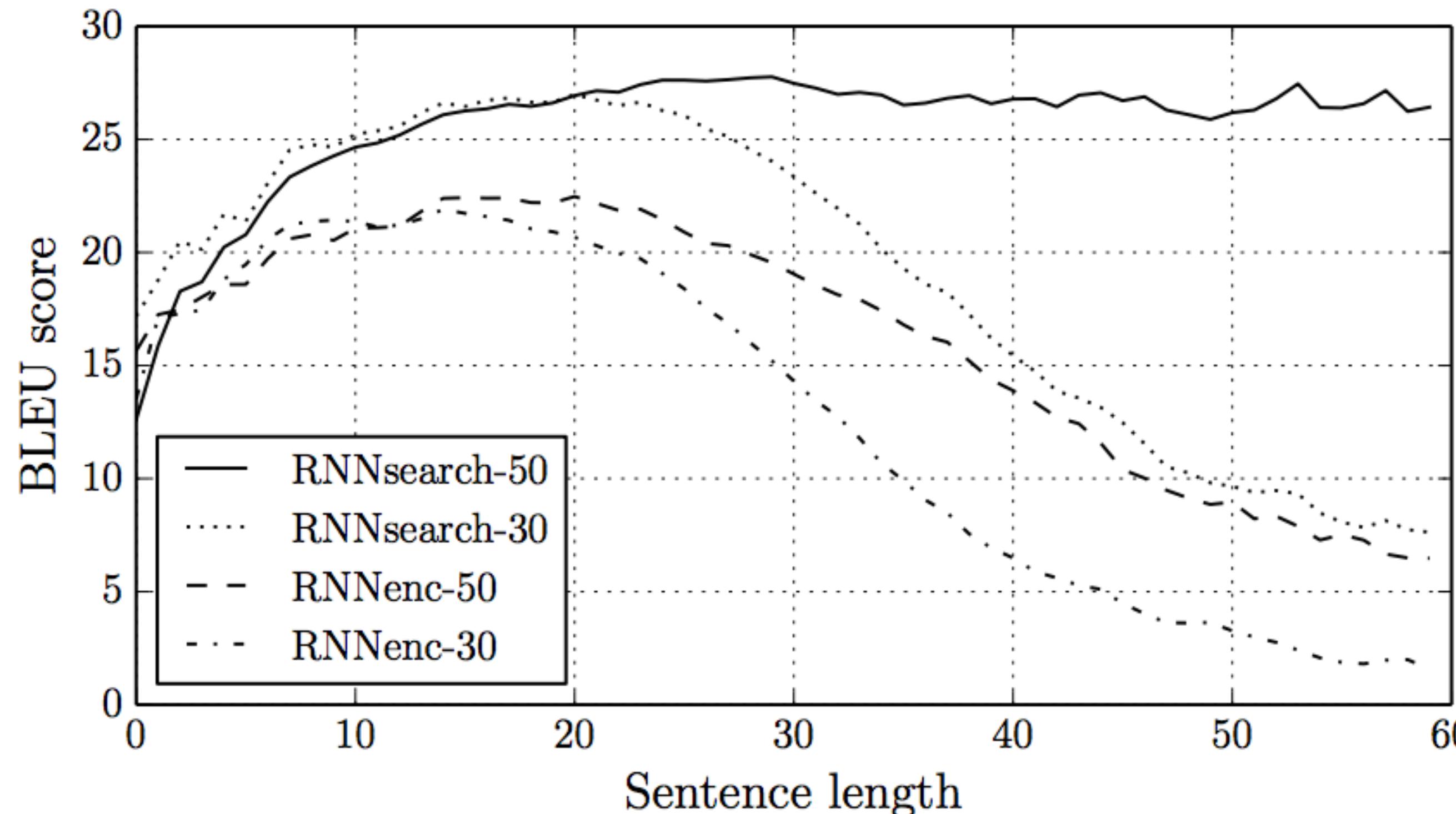
fr: Le portique écotaxe de Pont-de-Buis , ... [truncated] ..., a été démonté jeudi matin

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

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

the movie was great

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

the movie was great

| / / /

le film était bon

Aligned Inputs

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

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

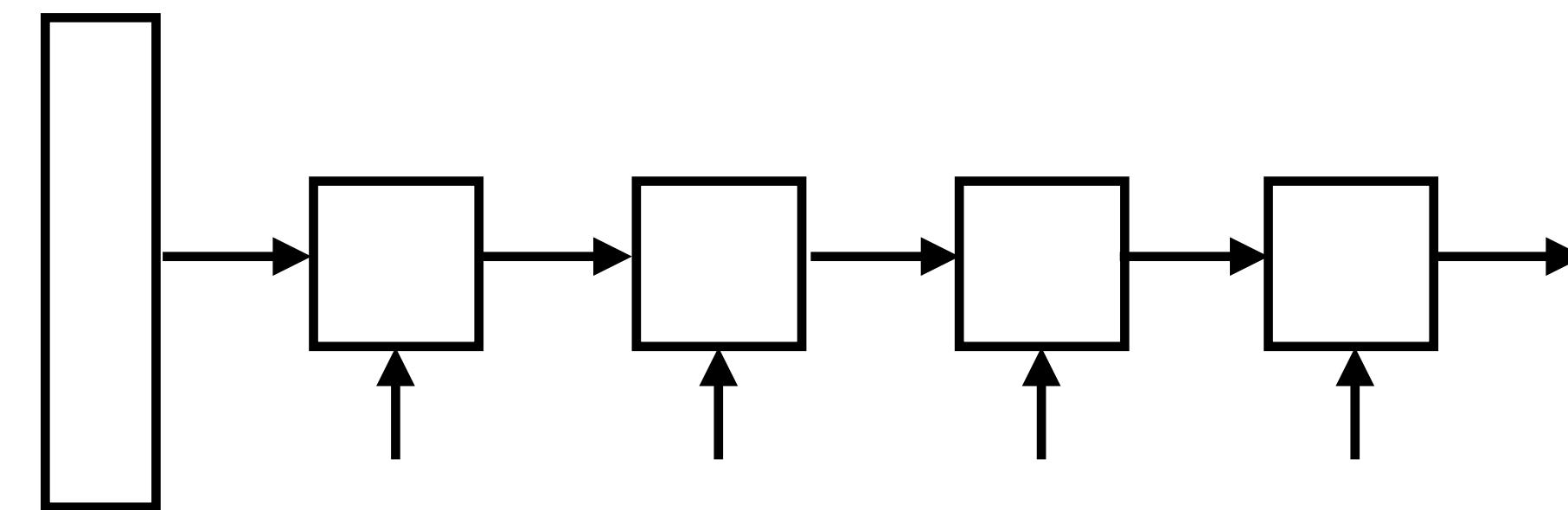
- ▶ Can look at the corresponding input word when translating — this could scale!

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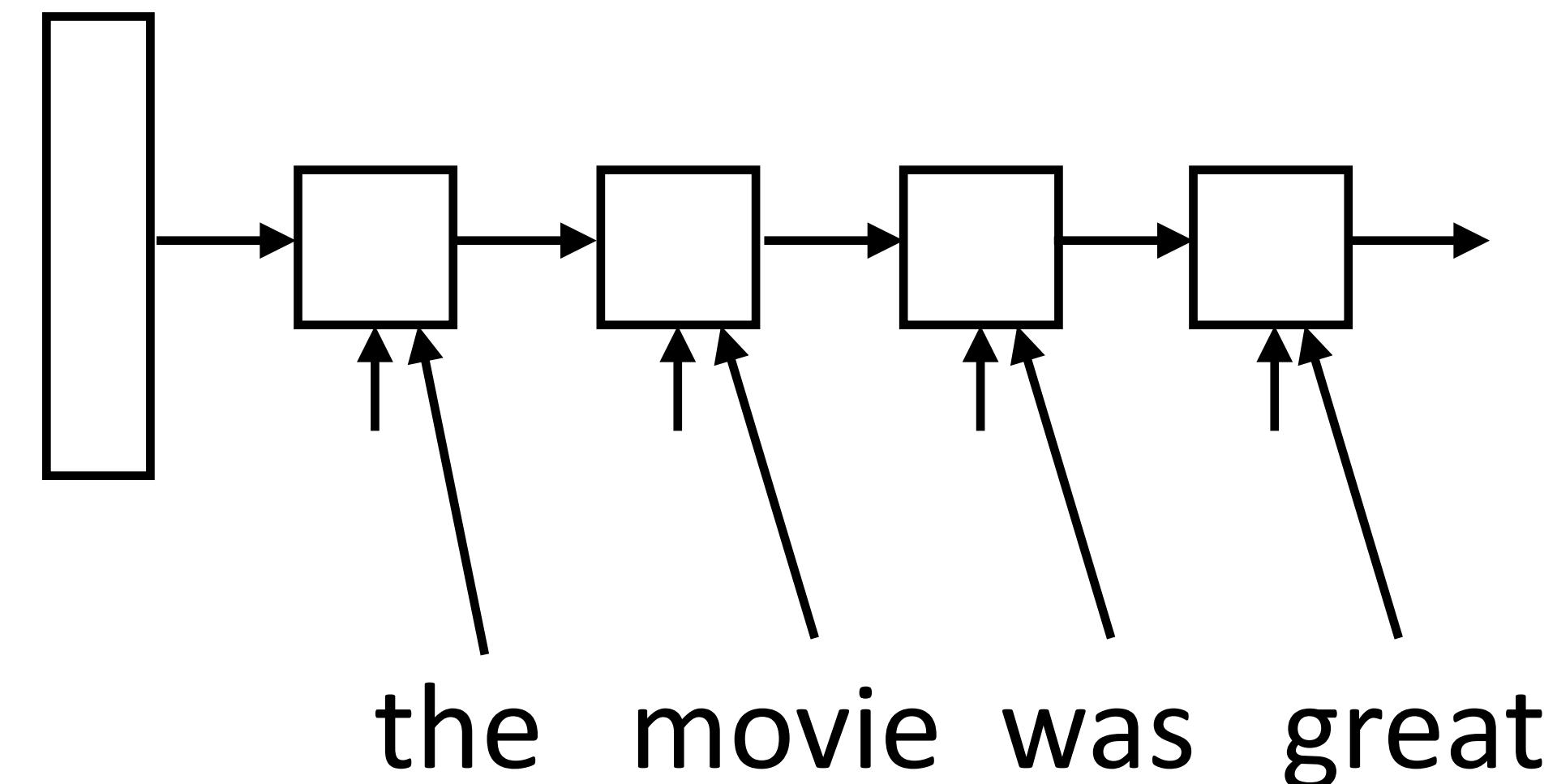


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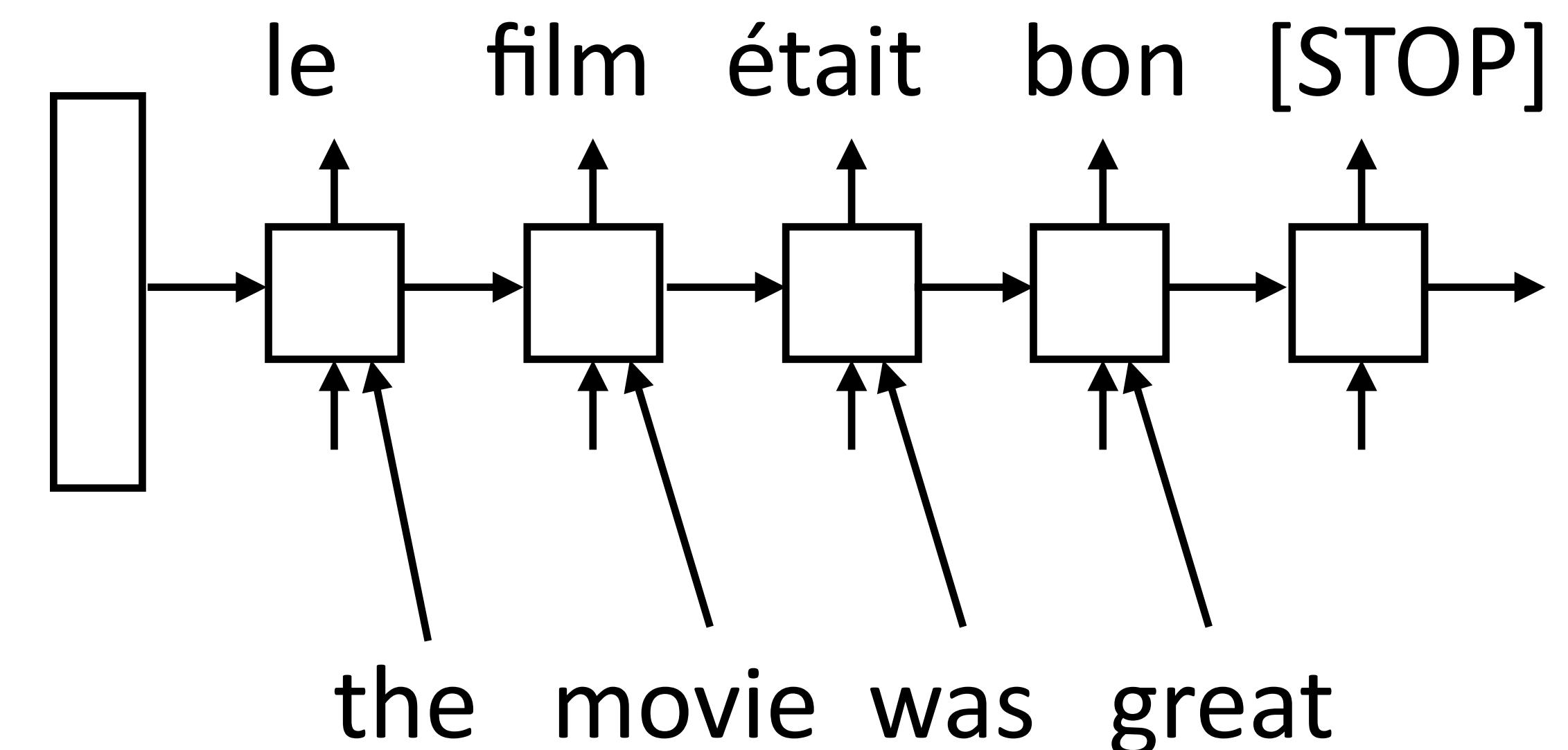


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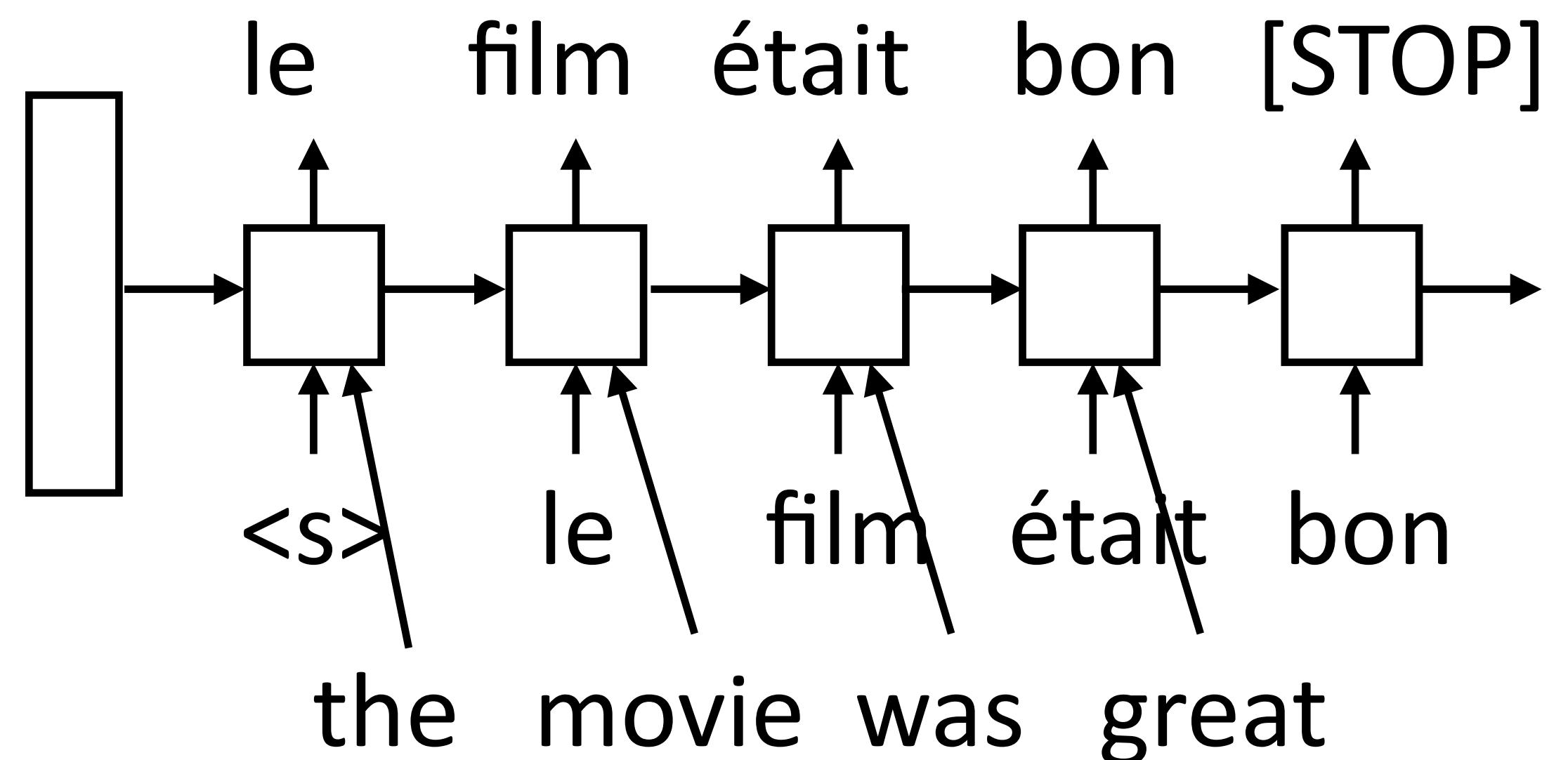


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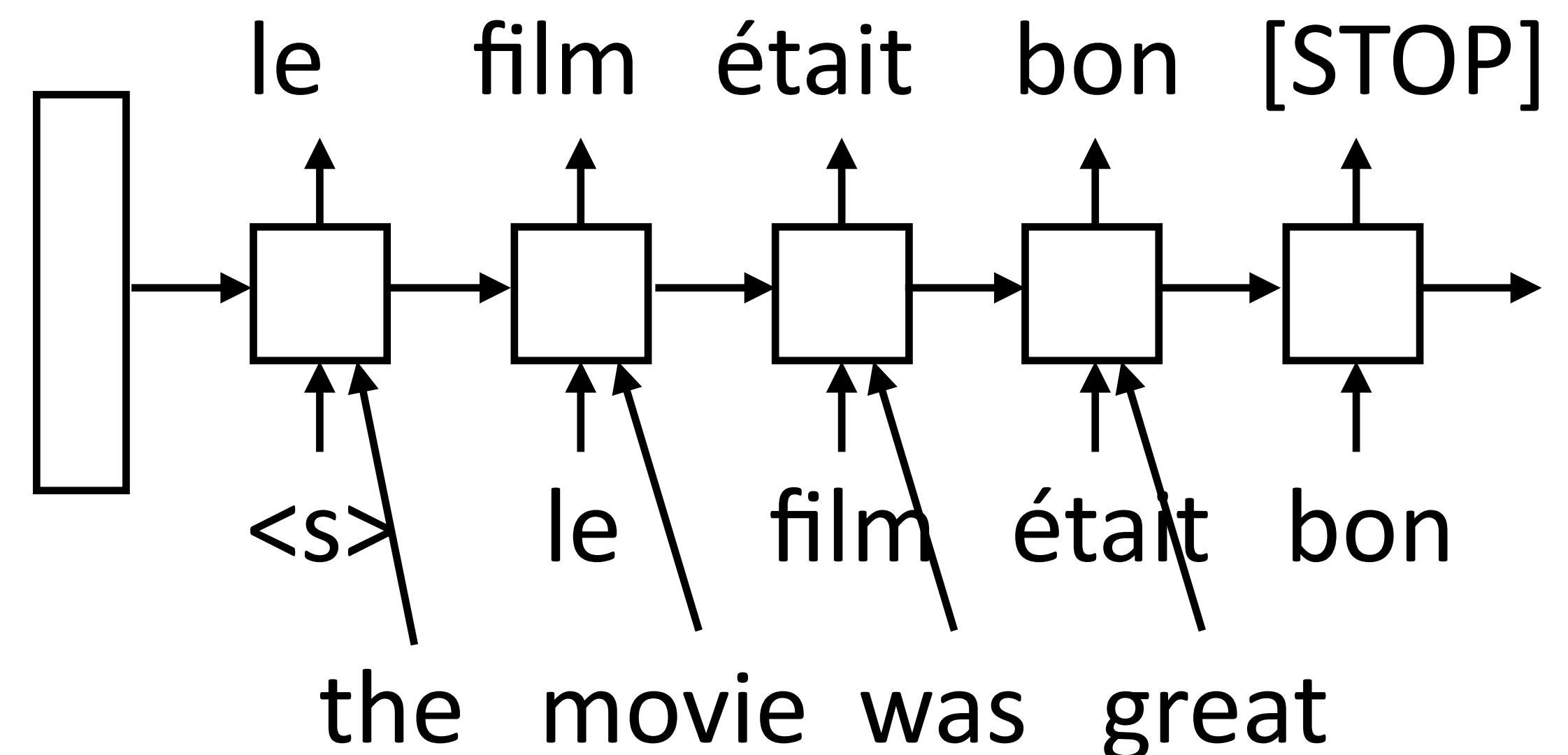
Aligned Inputs

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

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

- ▶ Much less burden on the hidden state



Aligned Inputs

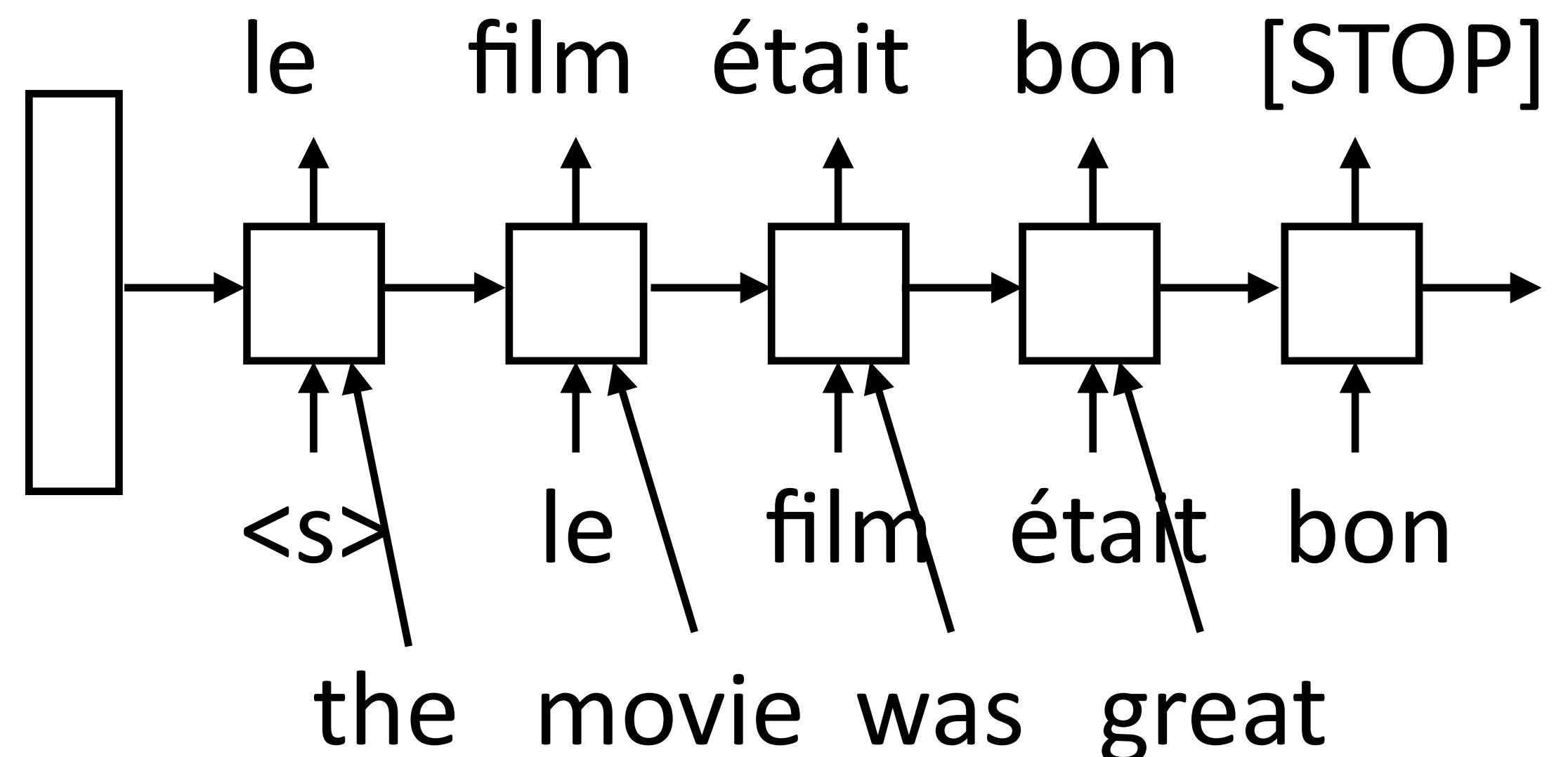
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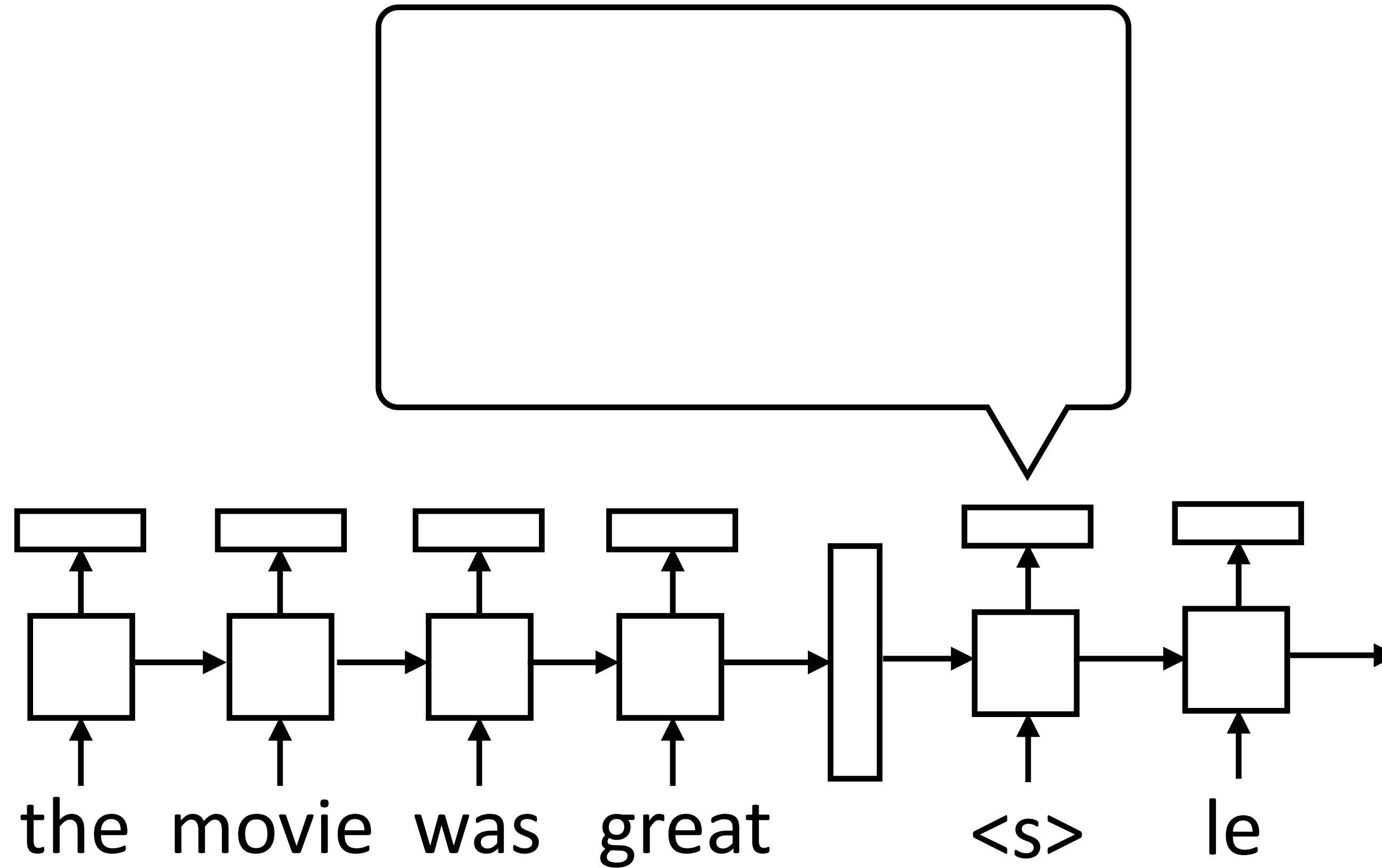
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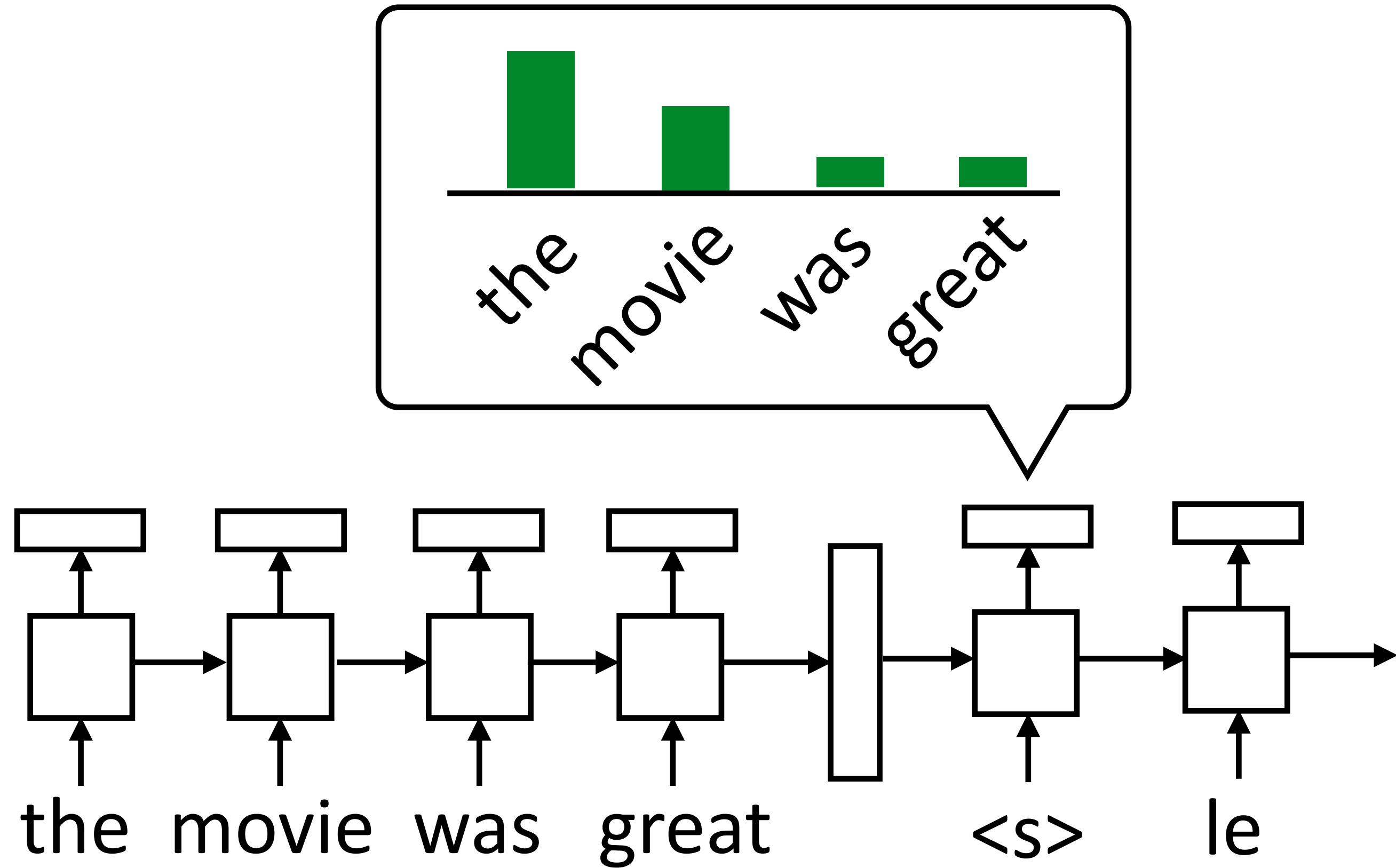
- ▶ How can we achieve this without hardcoding it?



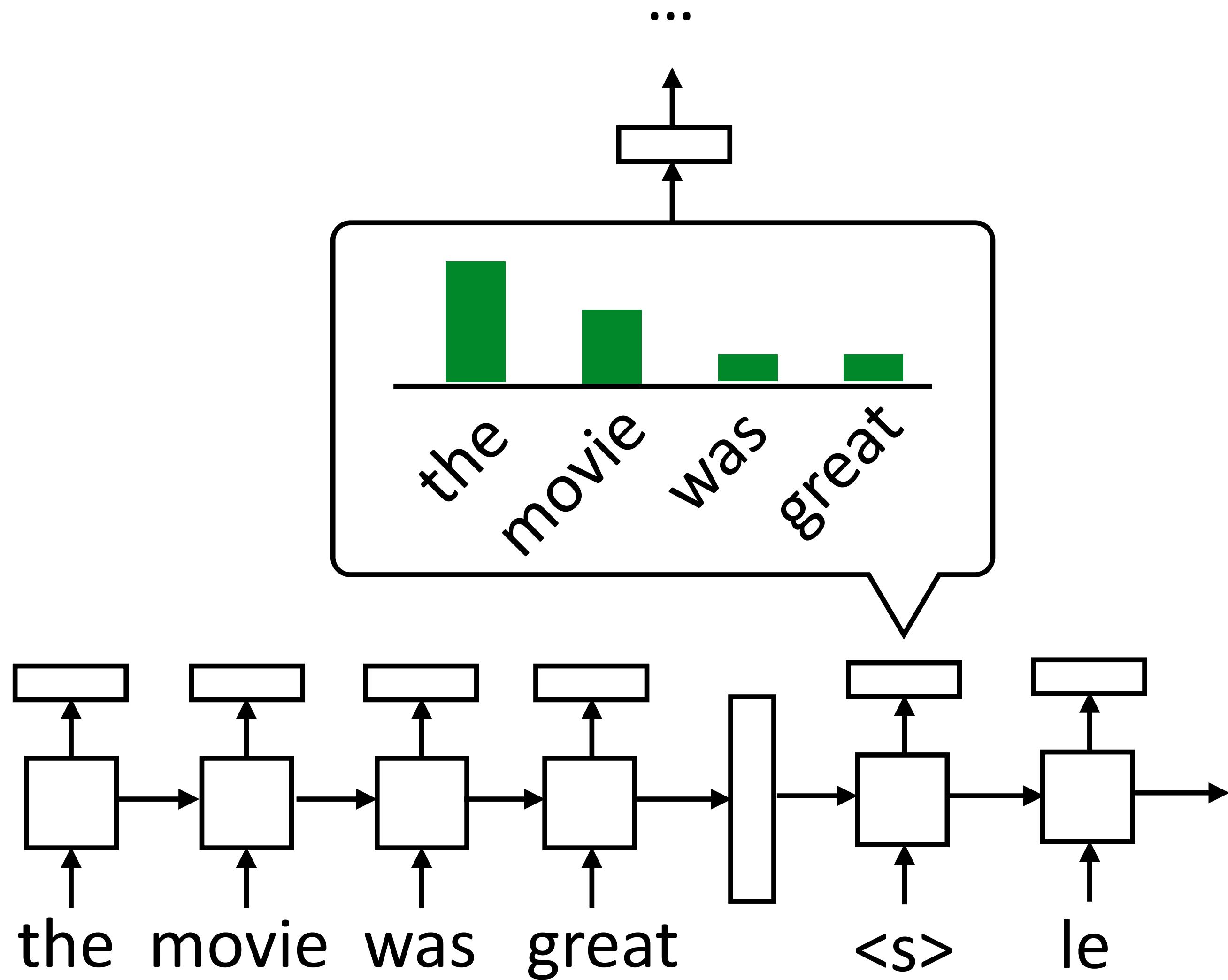
Attention



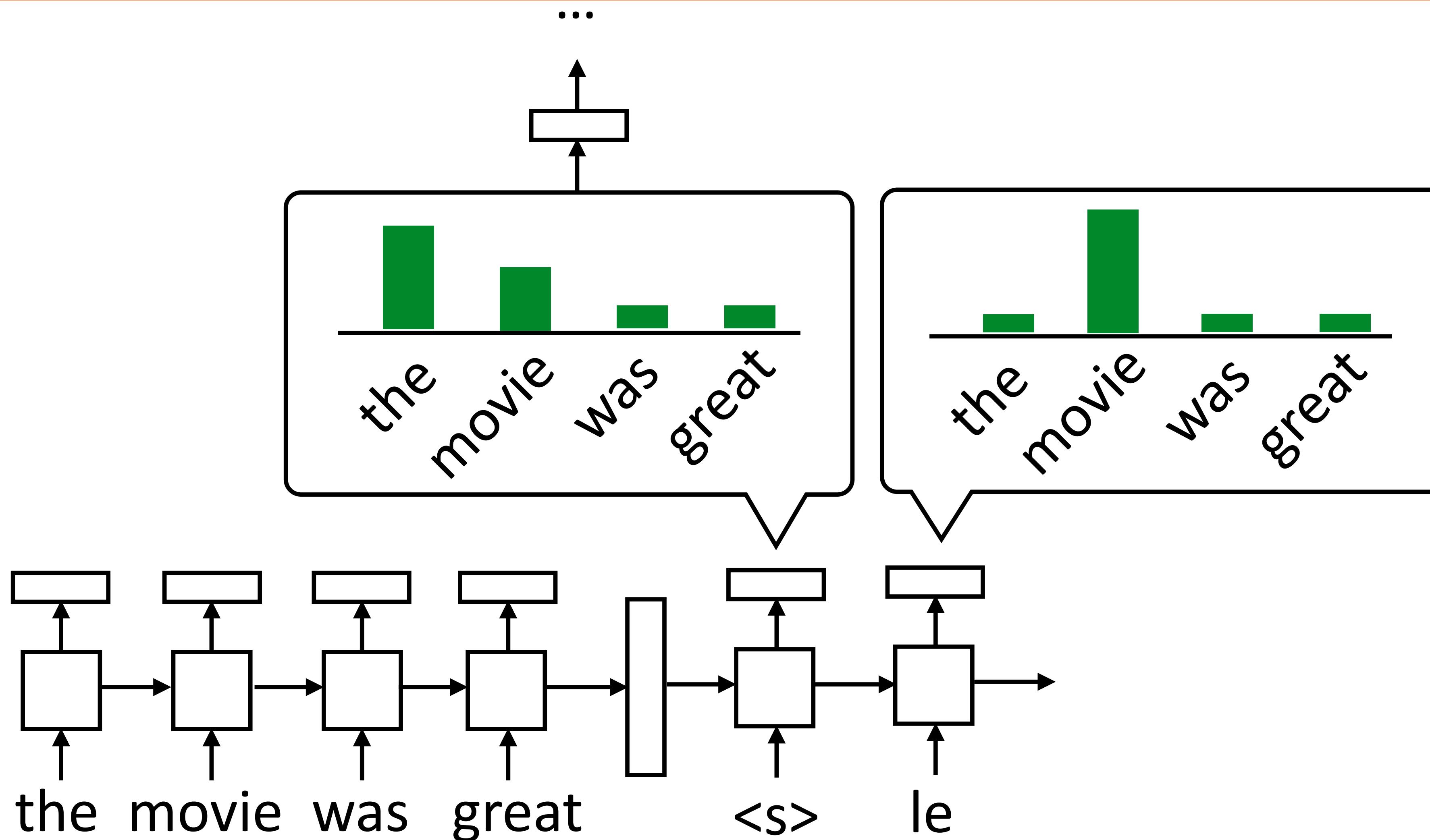
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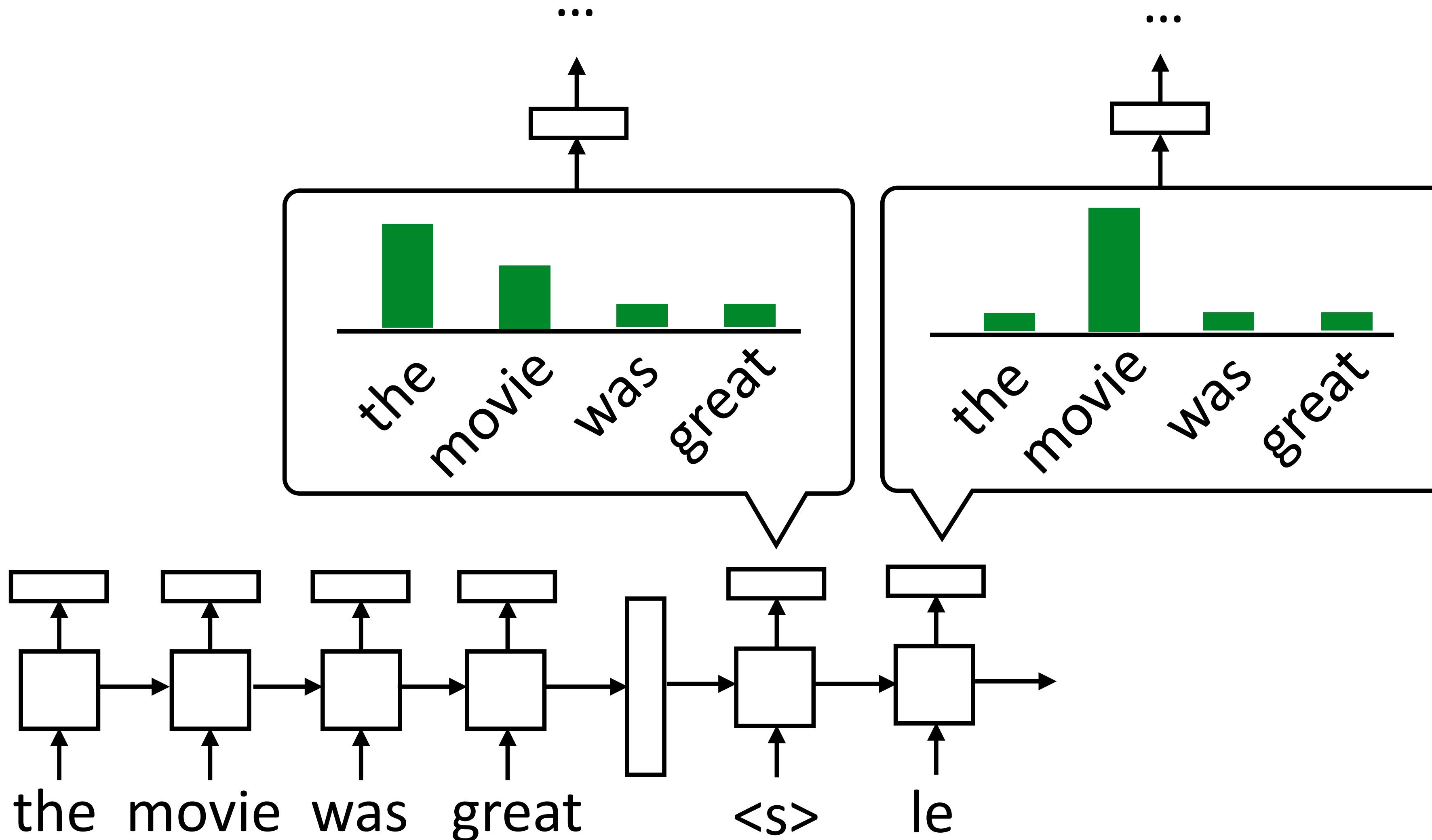
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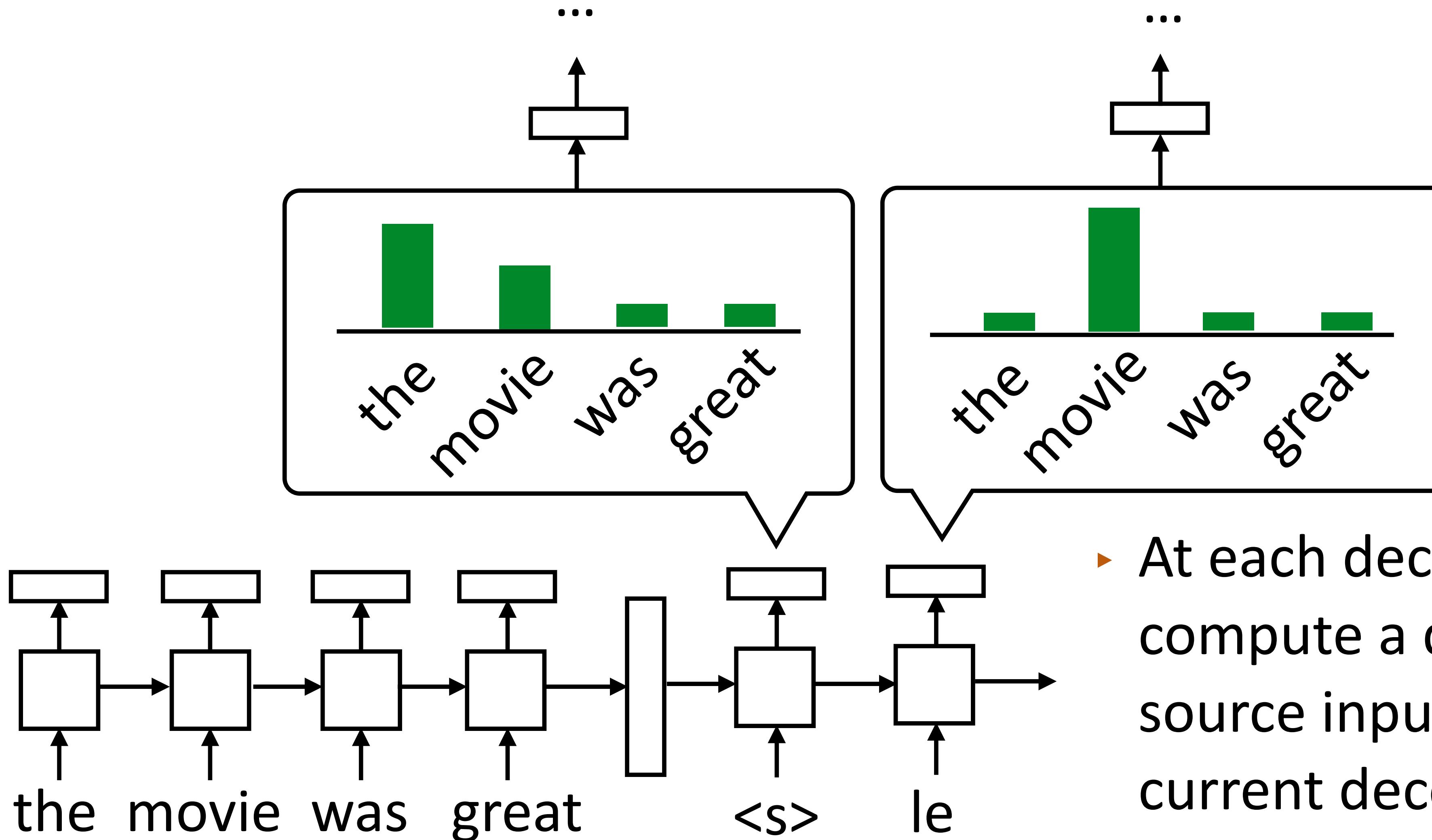
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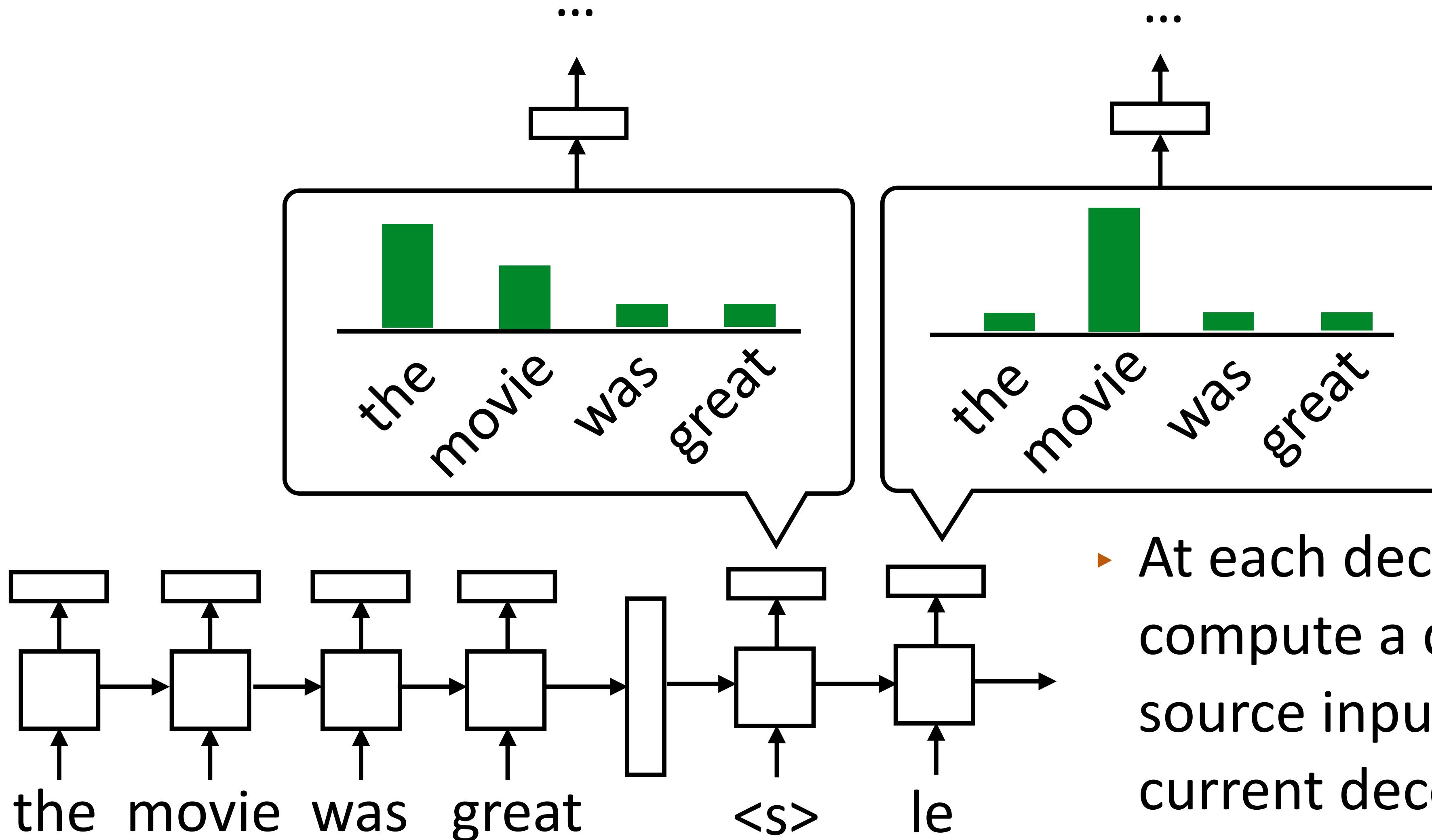
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Attention



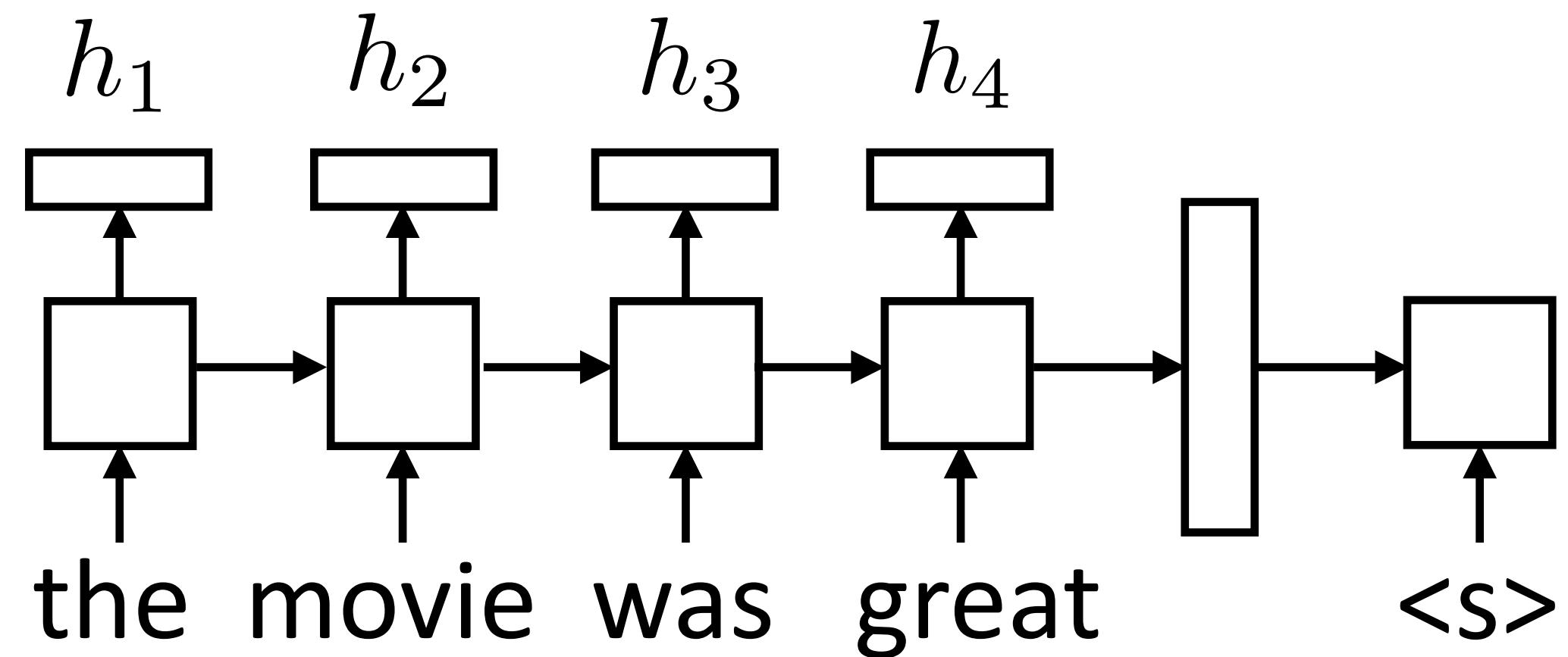
Attention



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

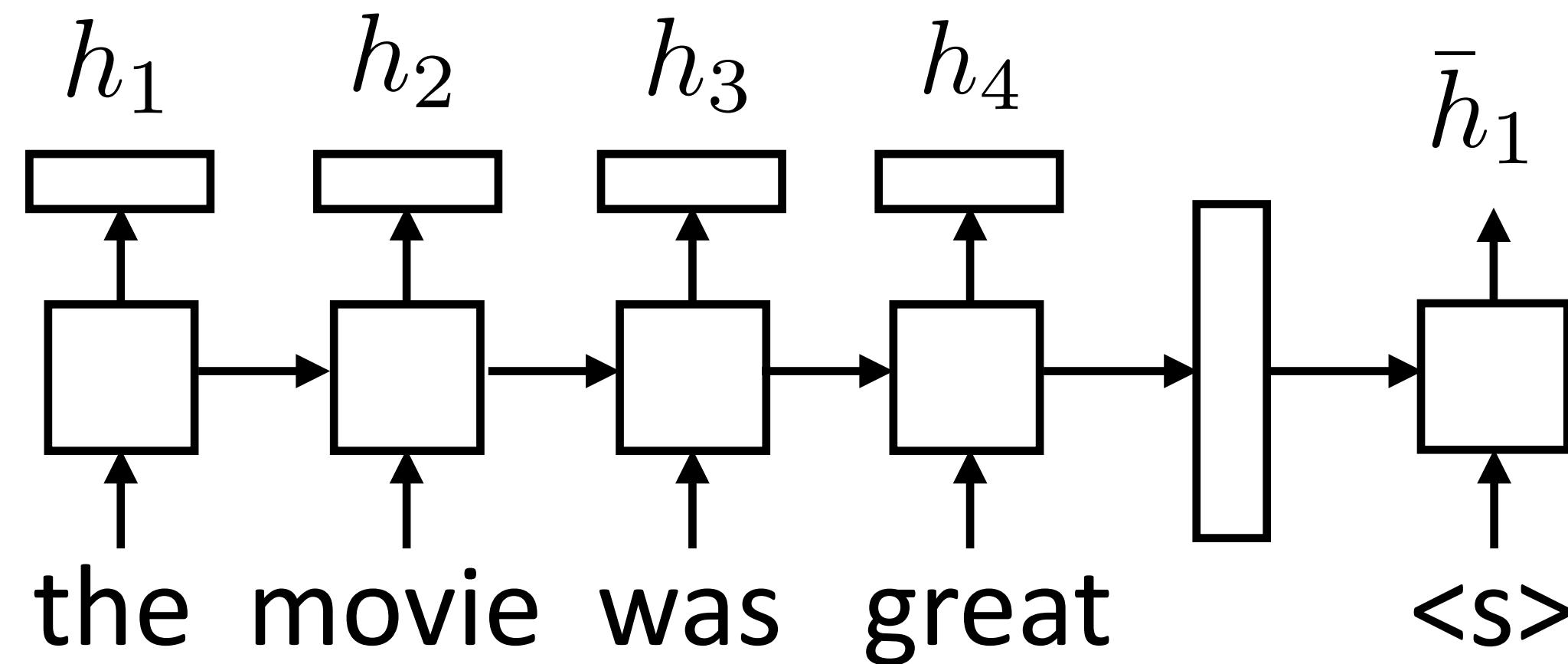
Attention

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



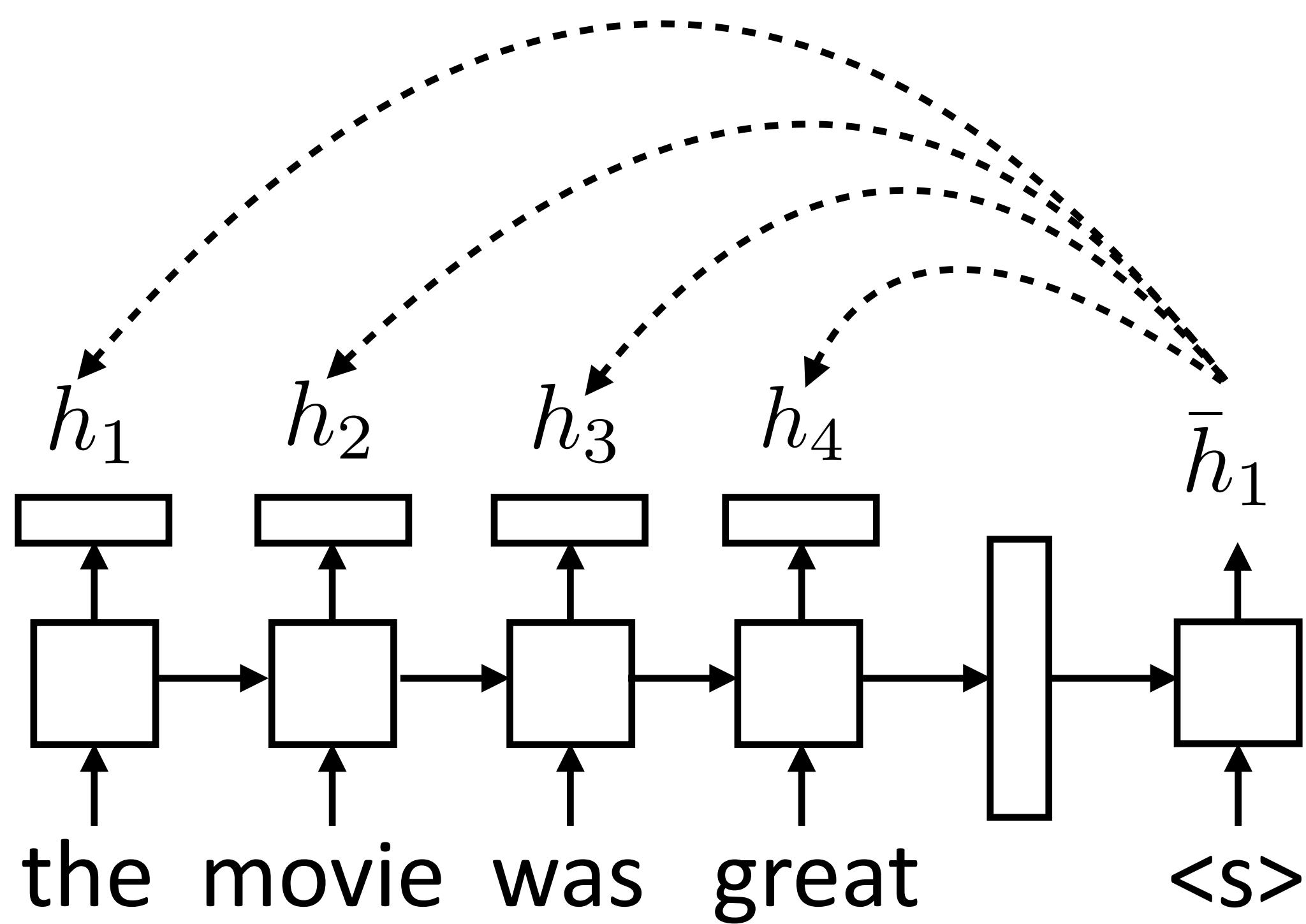
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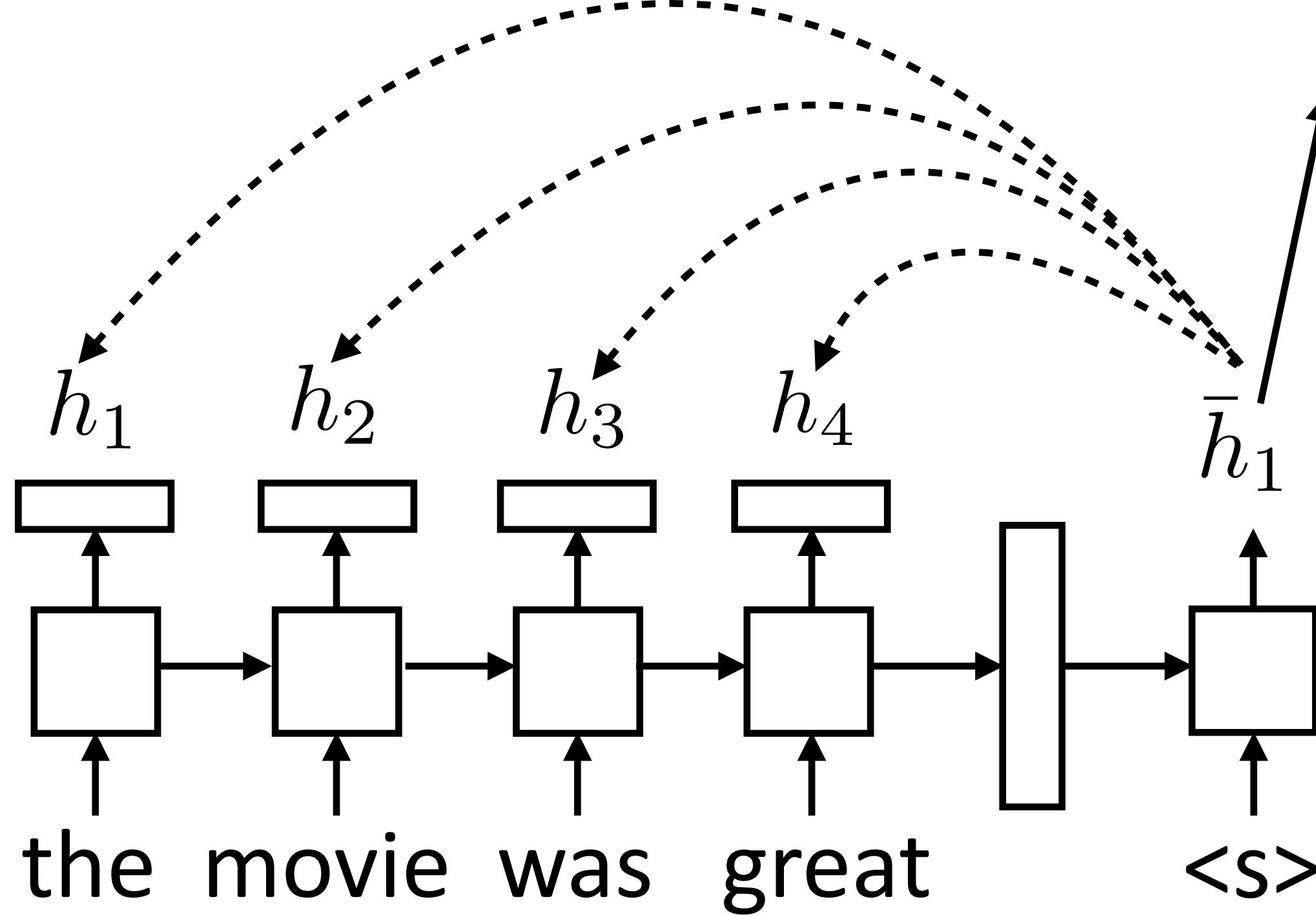
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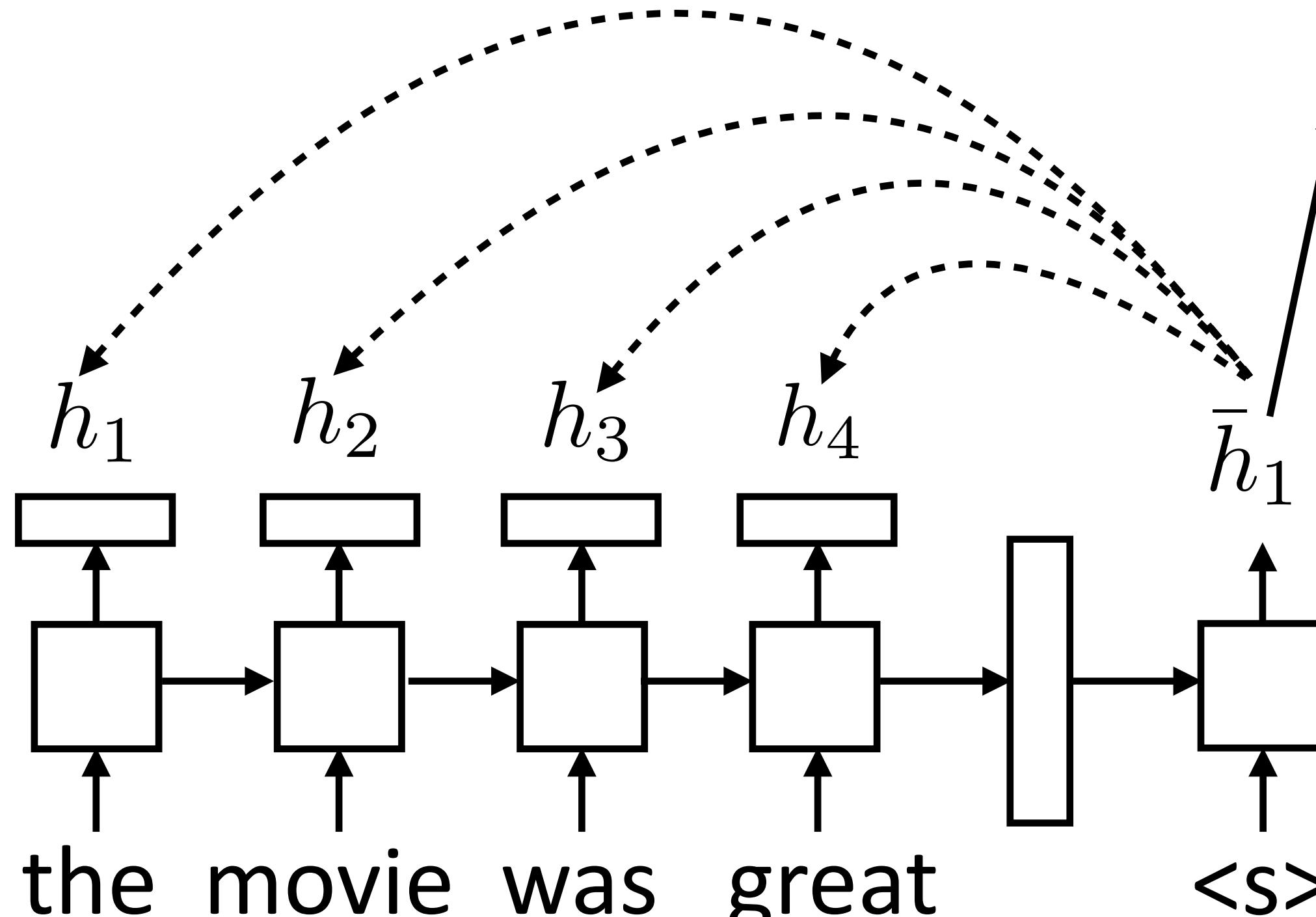
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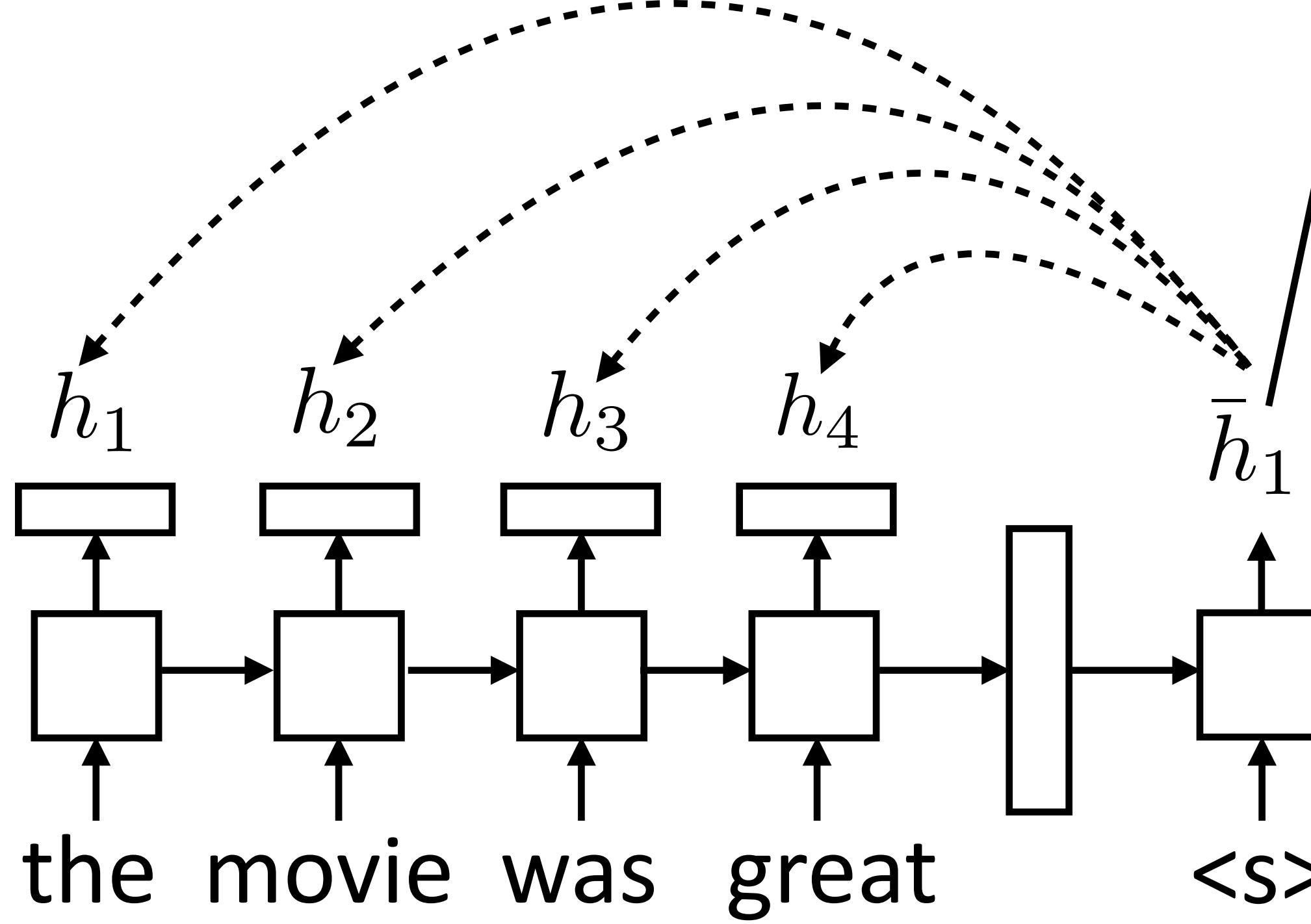


$$e_{ij} = f(\bar{h}_i, h_j)$$

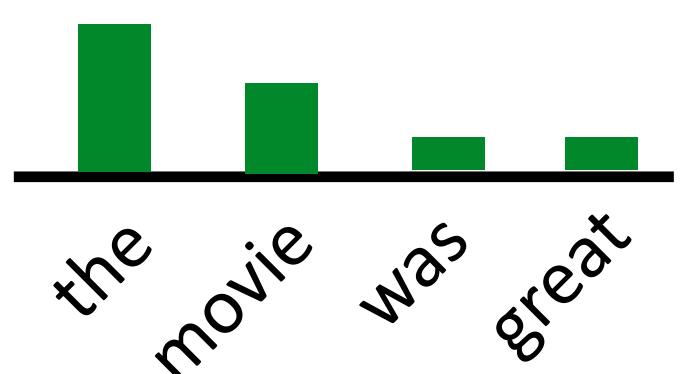
- ▶ Unnormalized scalar weight

Attention

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



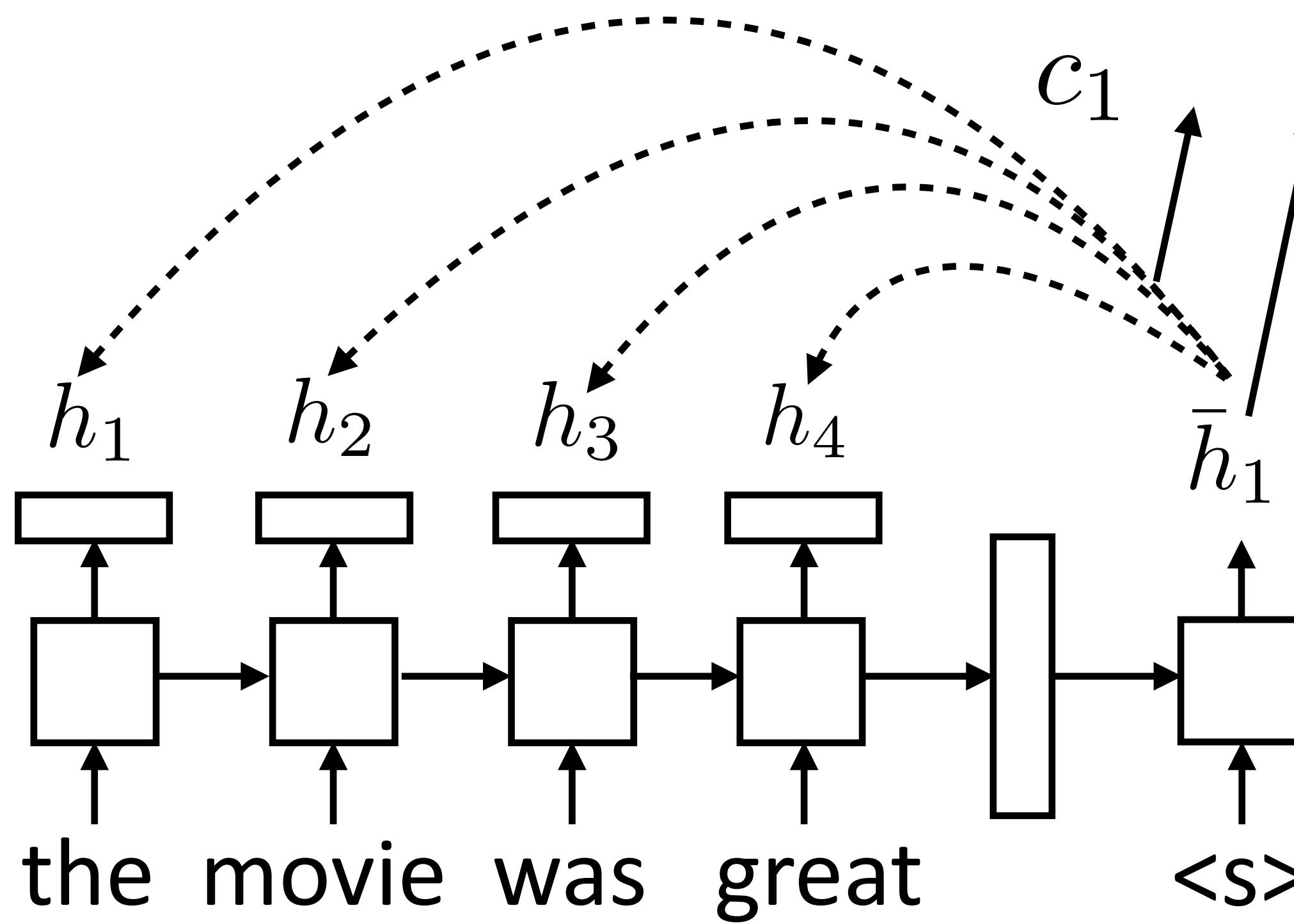
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$
$$e_{ij} = f(\bar{h}_i, h_j)$$



- ▶ Unnormalized scalar weight

Attention

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compute weighted sum of
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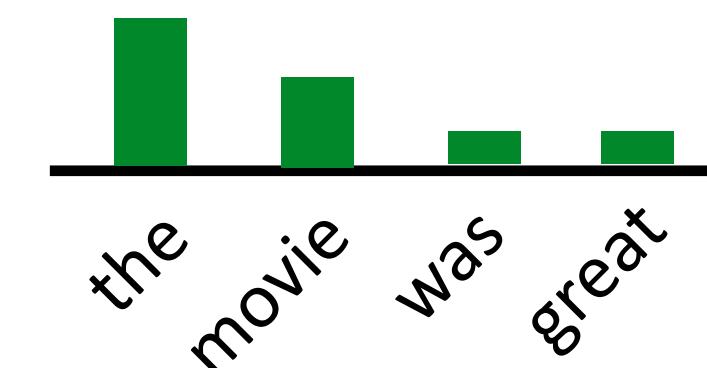


$$c_i = \sum_j \alpha_{ij} h_j$$

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

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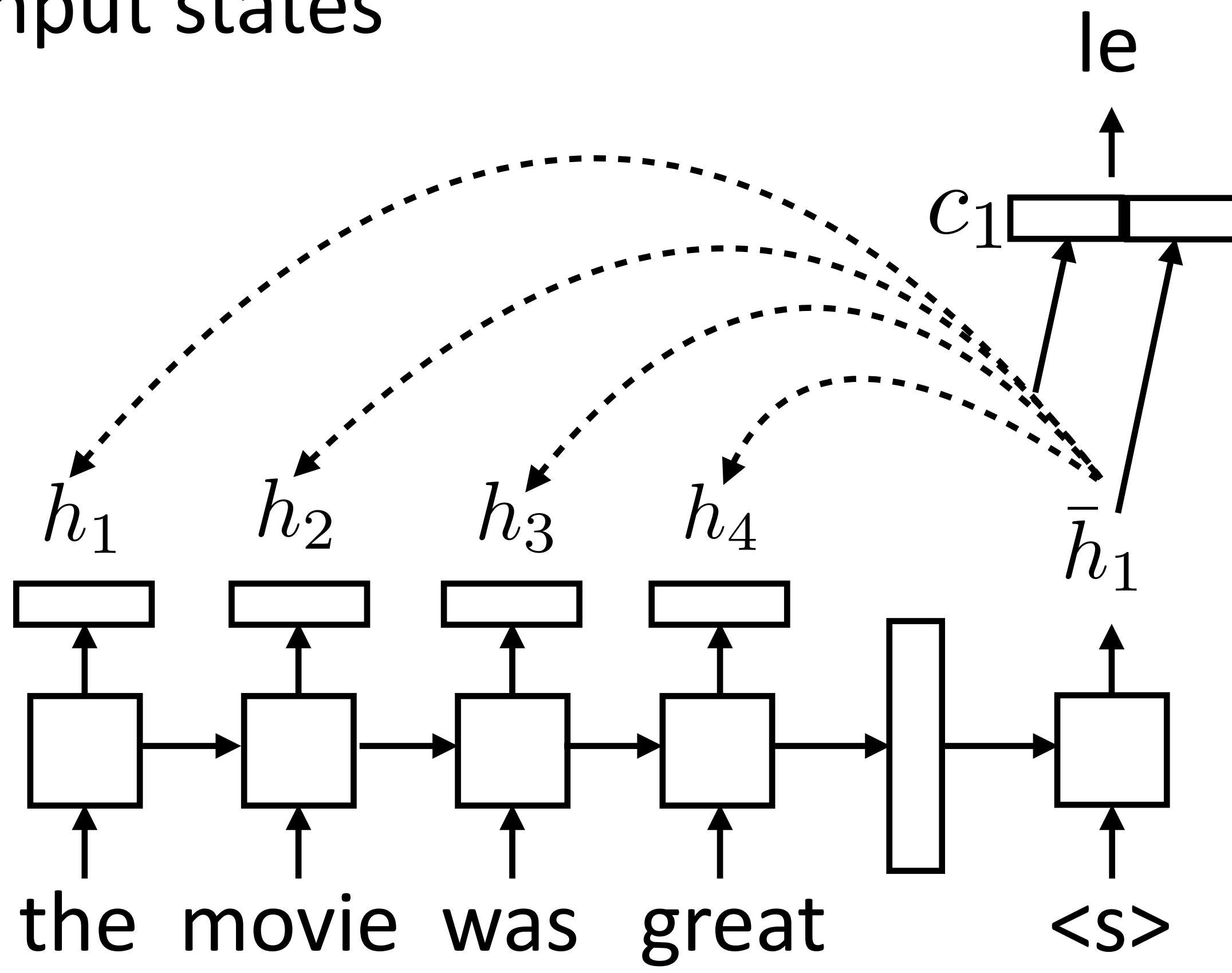
- ▶ Weighted sum
of input hidden
states (vector)



- ▶ Unnormalized
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Attention

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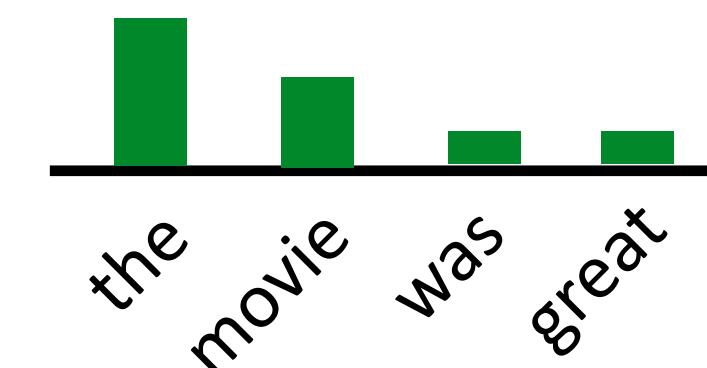


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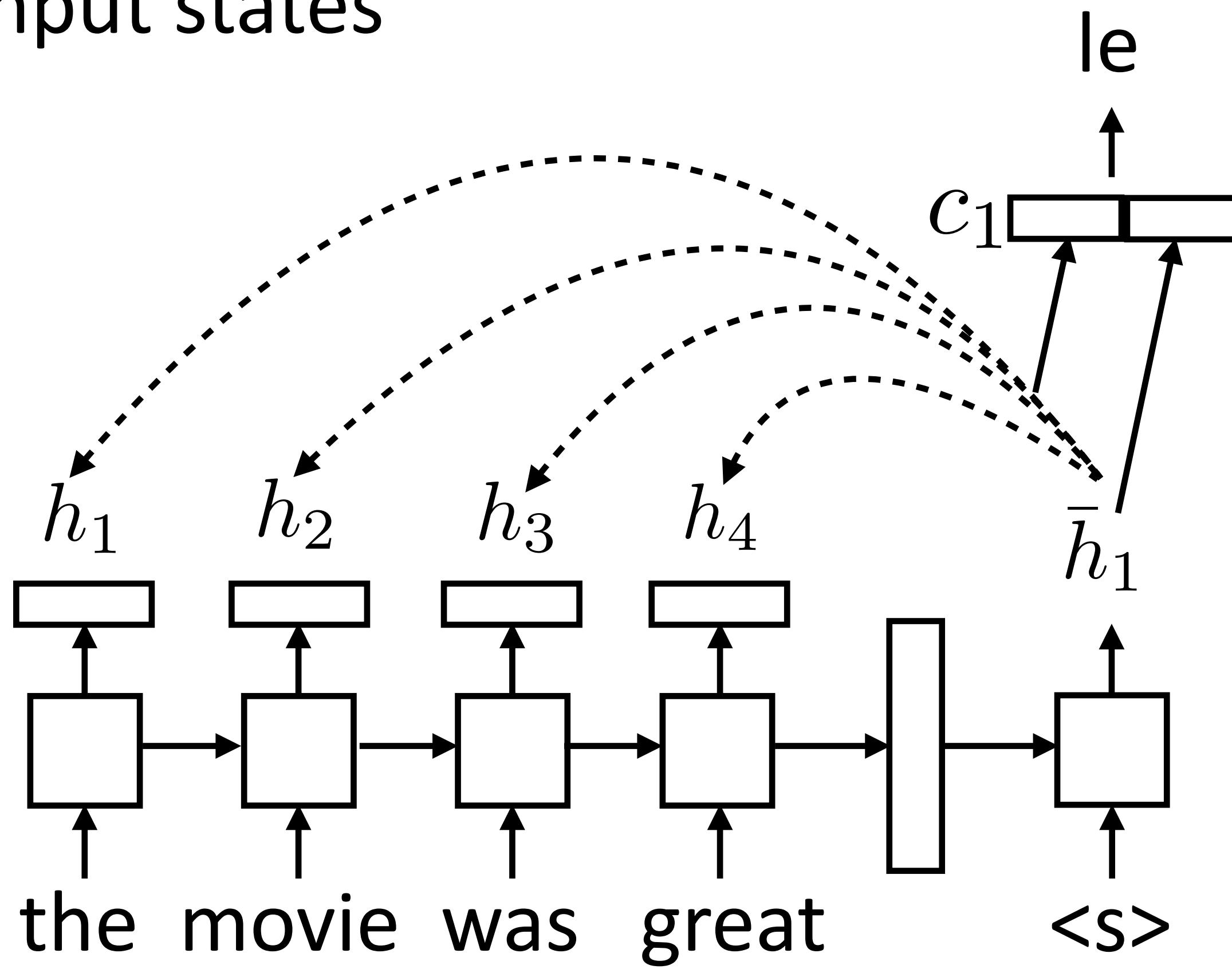
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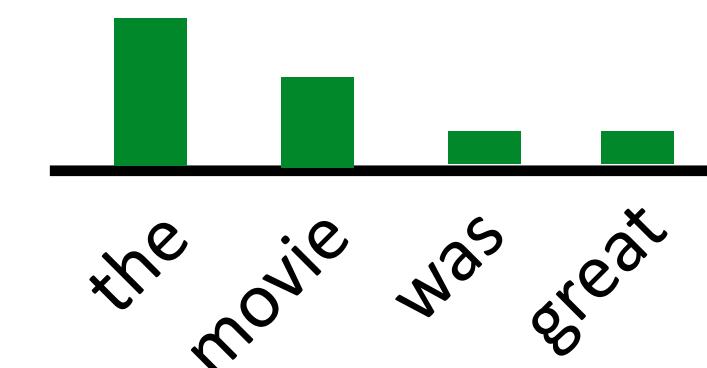
$$P(y_i | \mathbf{x}, y_1, \dots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$

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

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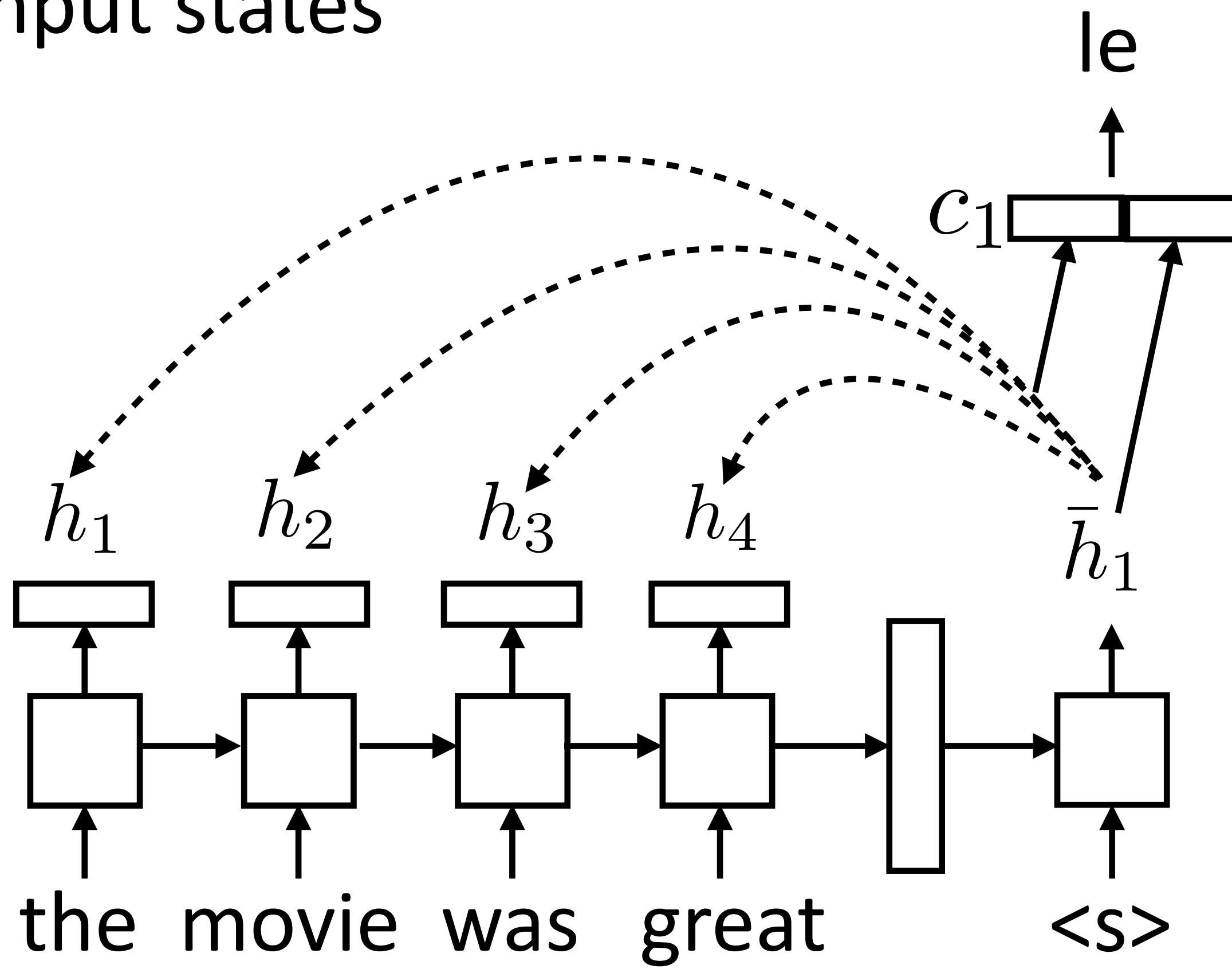
- ▶ Weighted sum
of input hidden
states (vector)



- ▶ Unnormalized
scalar weight

Attention

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



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

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

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

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

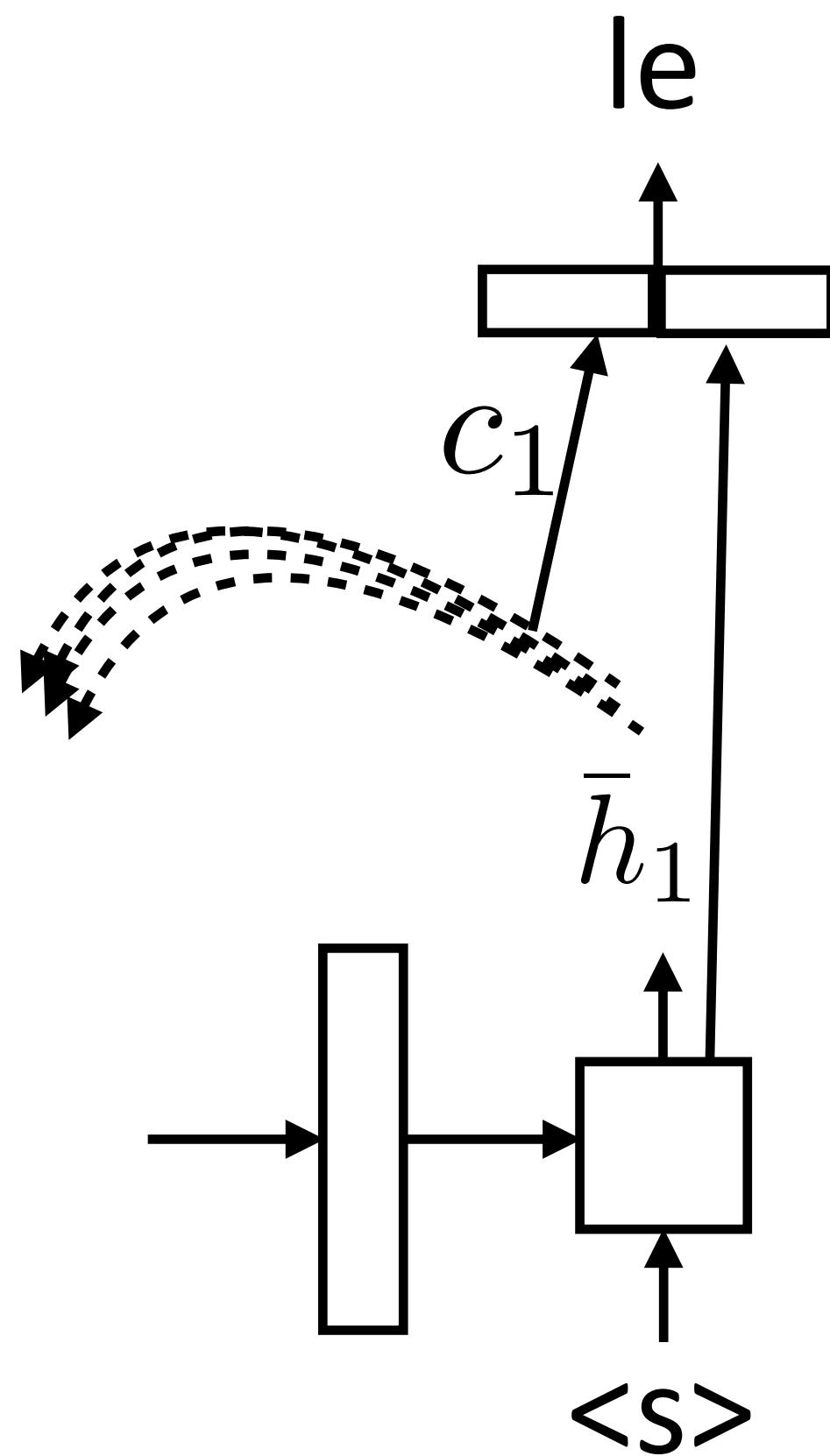
$$e_{ij} = f(\bar{h}_i, h_j)$$

- ▶ Weighted sum of input hidden states (vector)



- ▶ Unnormalized scalar weight

Attention

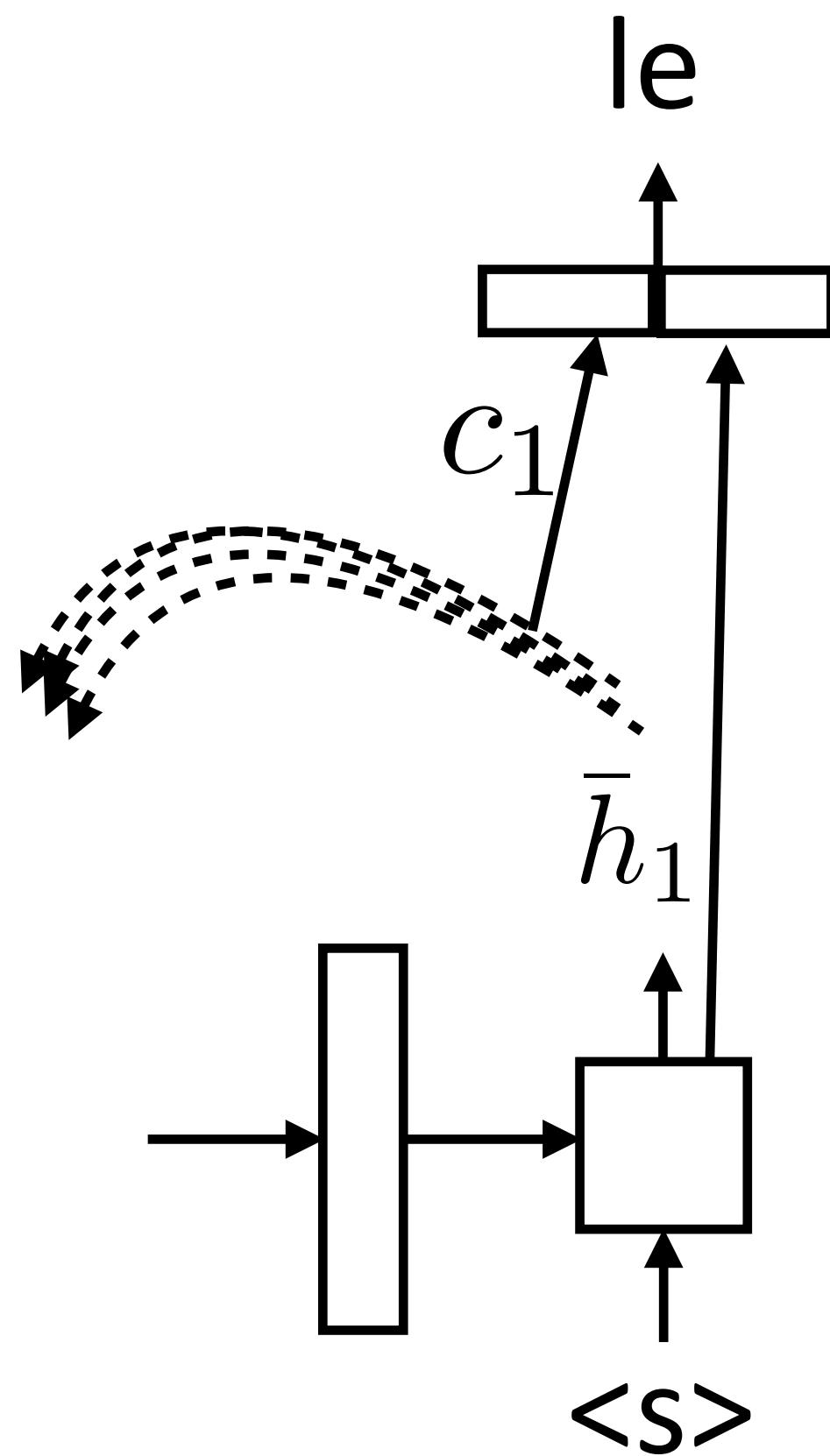


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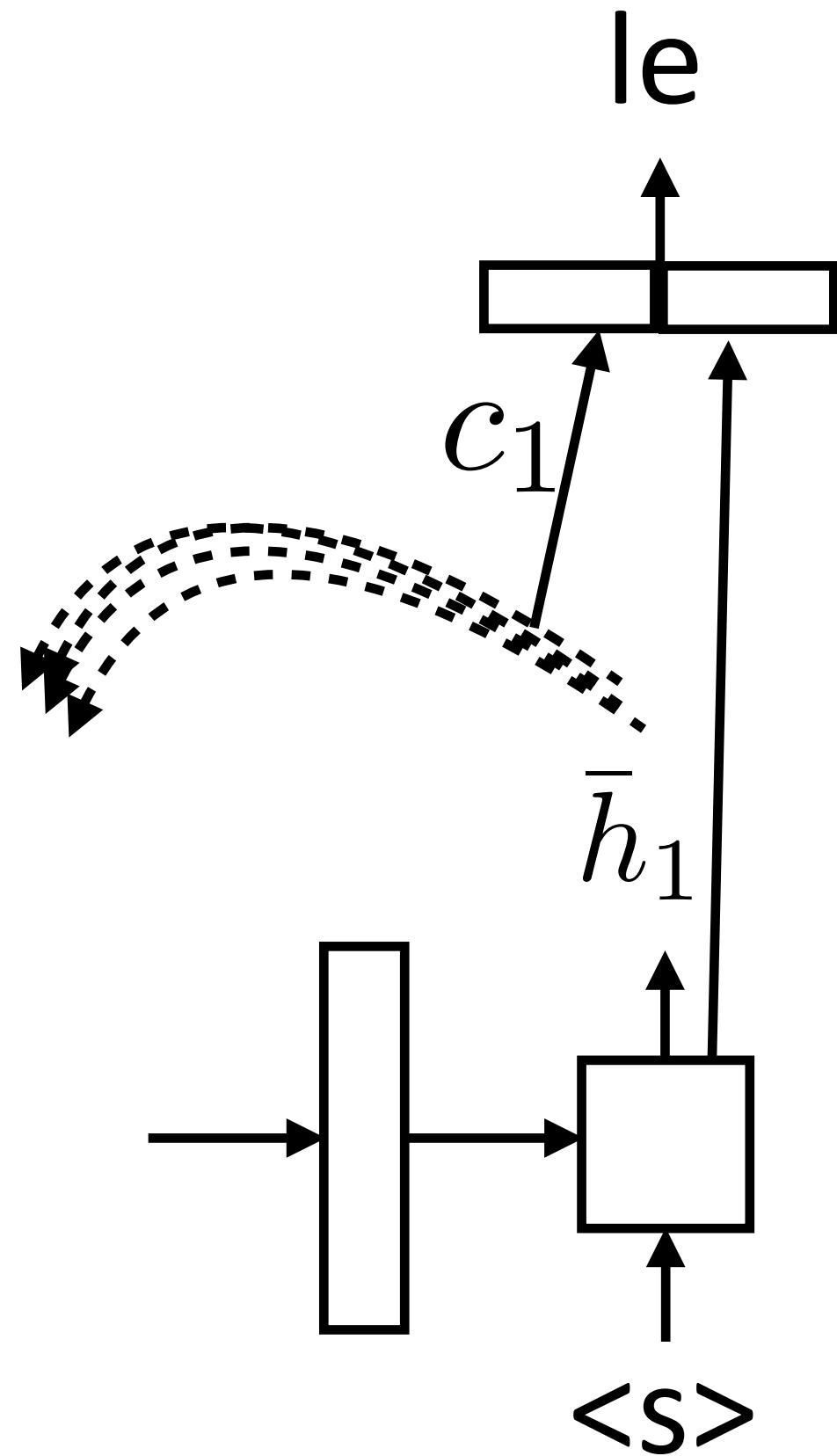
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► Bahdanau+ (2014): additive

Attention



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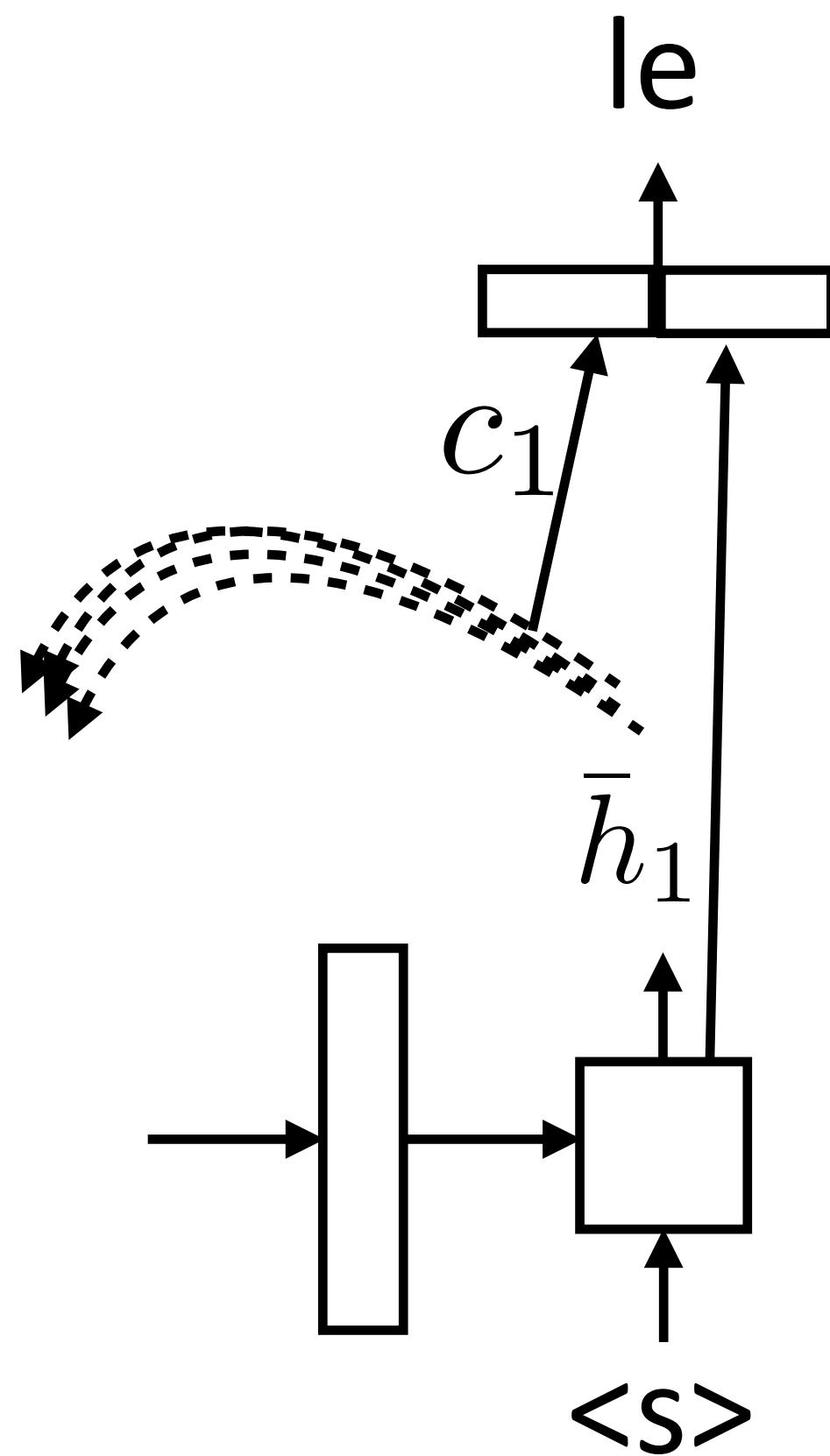
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$$f(\bar{h}_i, h_j) = \bar{h}_i \cdot h_j$$

► Luong+ (2015): dot product

Attention



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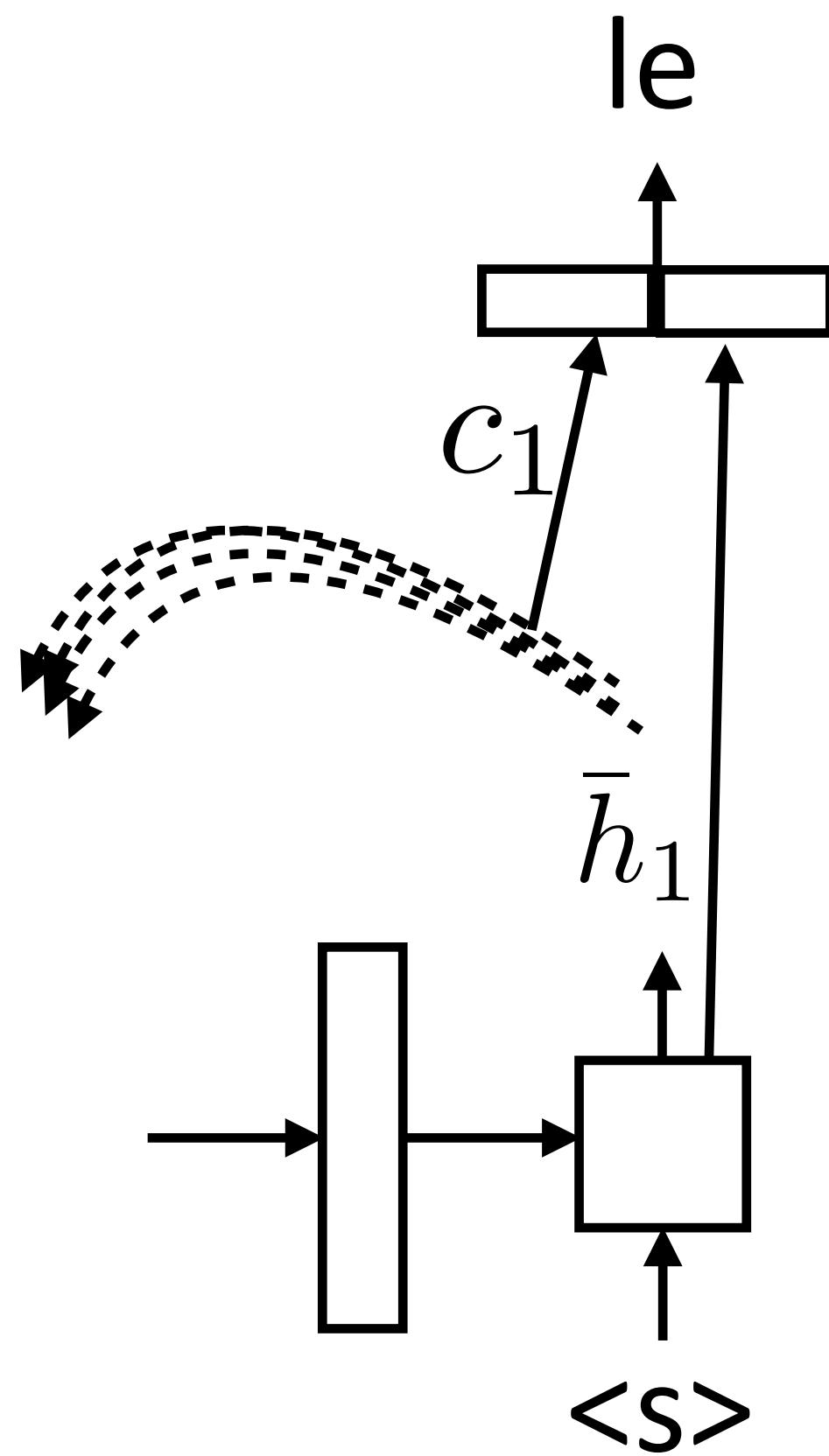
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► Luong+ (2015): dot product

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

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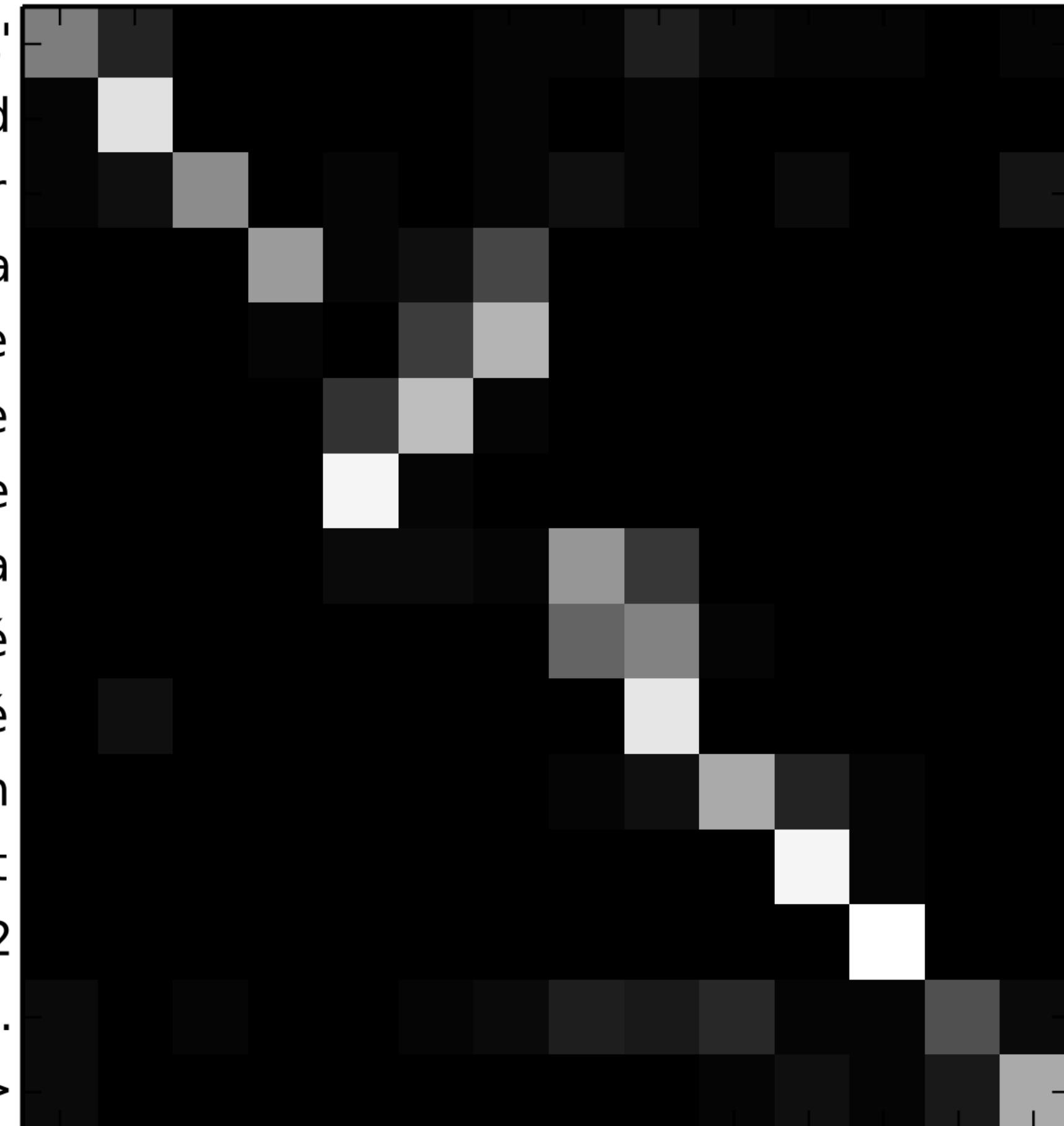
► Luong+ (2015): bilinear

- Note that this all uses outputs of hidden layers

Attention

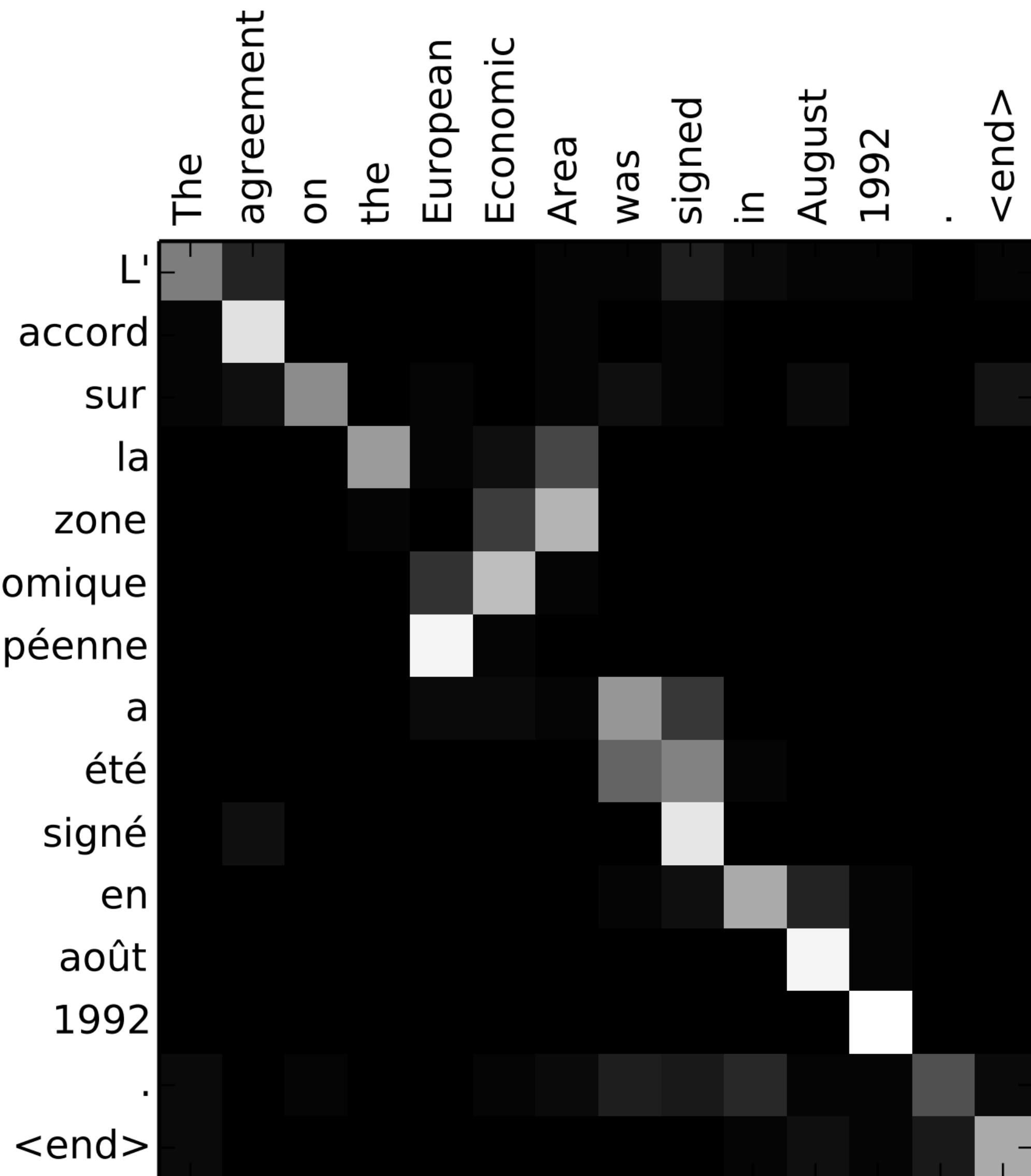
The agreement on the European Economic Area was signed in August 1992 . <end>

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



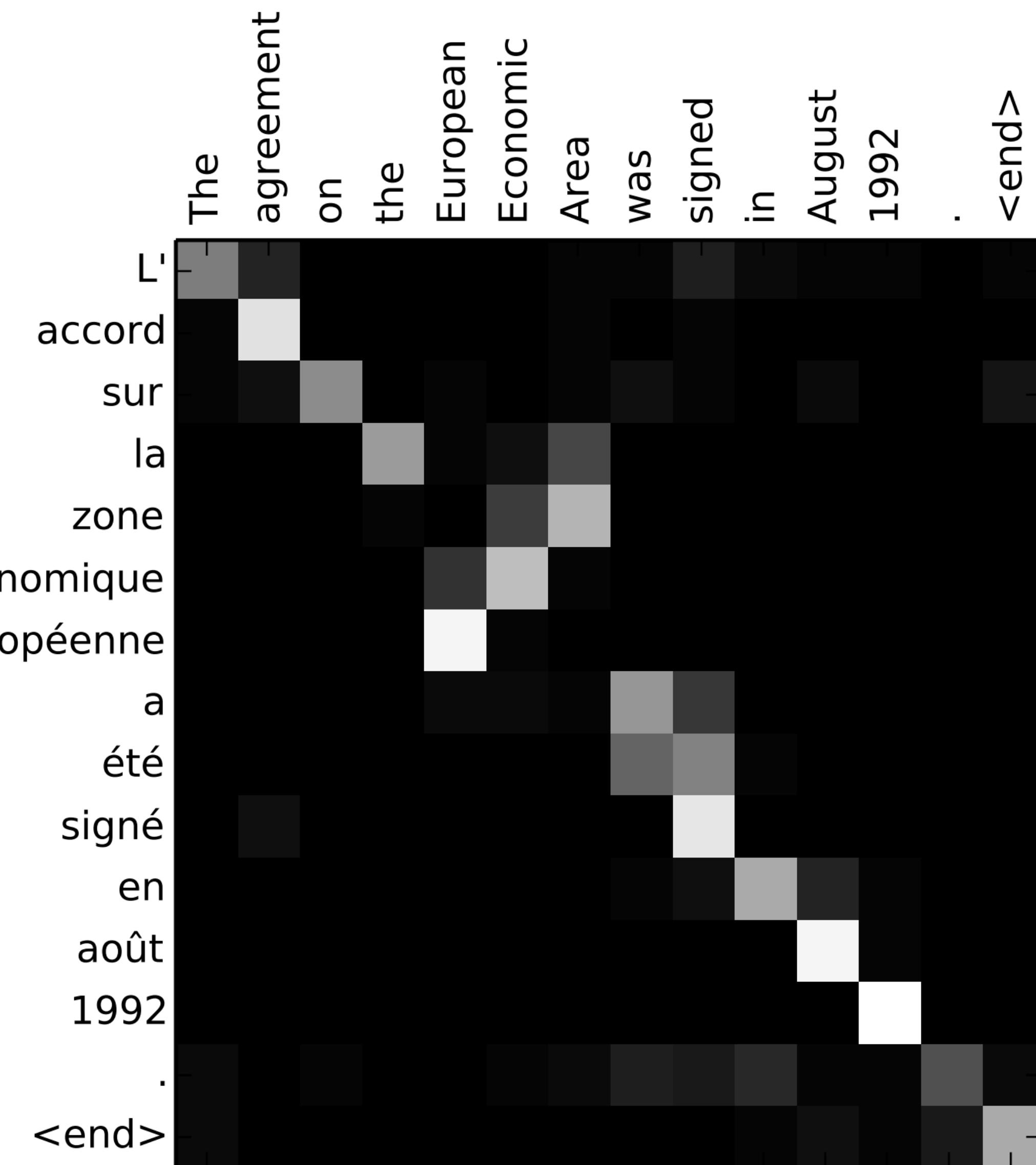
Attention

- ▶ Encoder hidden states capture contextual source word identity



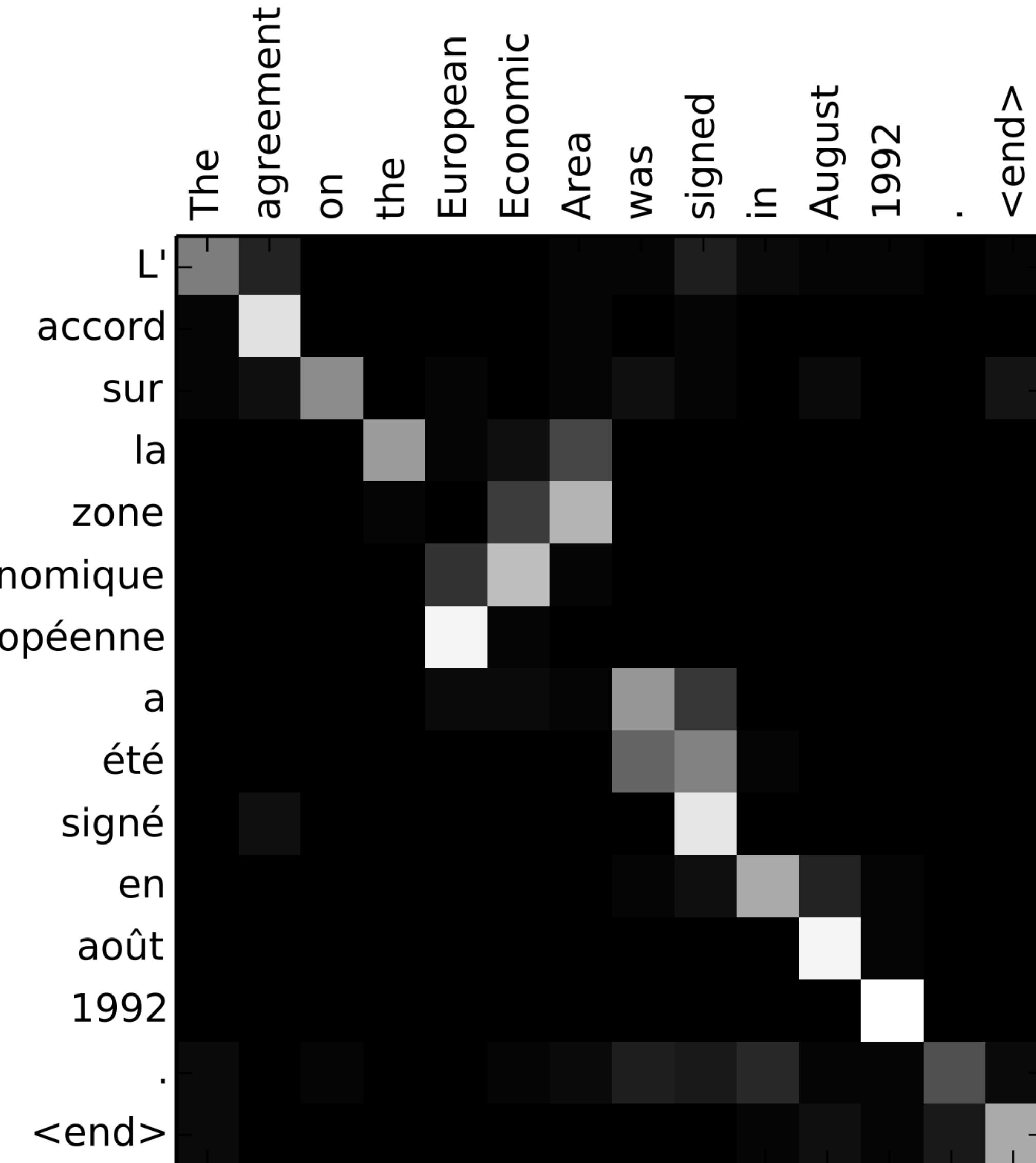
Attention

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



Attention

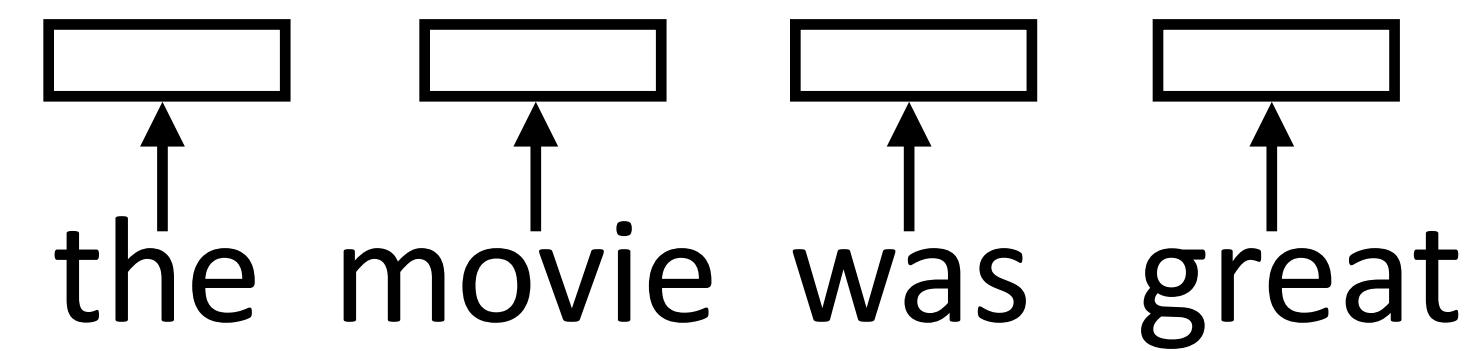
- ▶ Encoder hidden states capture contextual source word identity
- ▶ Decoder hidden states are now mostly responsible for selecting what to attend to
- ▶ Doesn't take a complex hidden state to walk monotonically through a sentence and spit out word-by-word translations



Transformers for MT

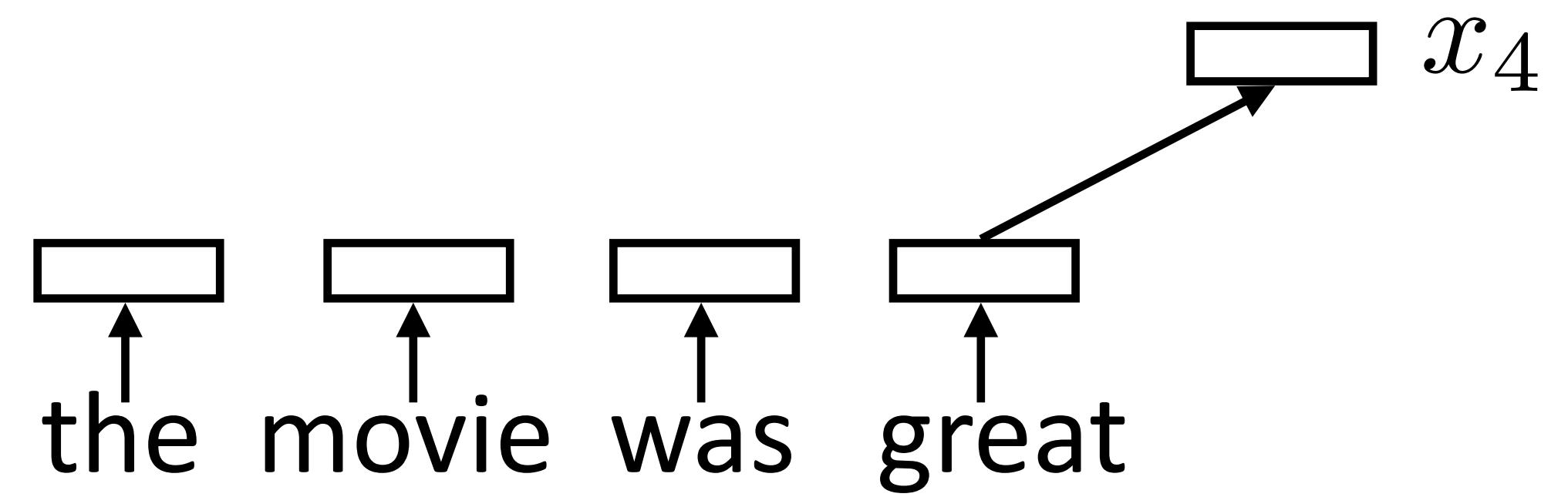
Self-Attention

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



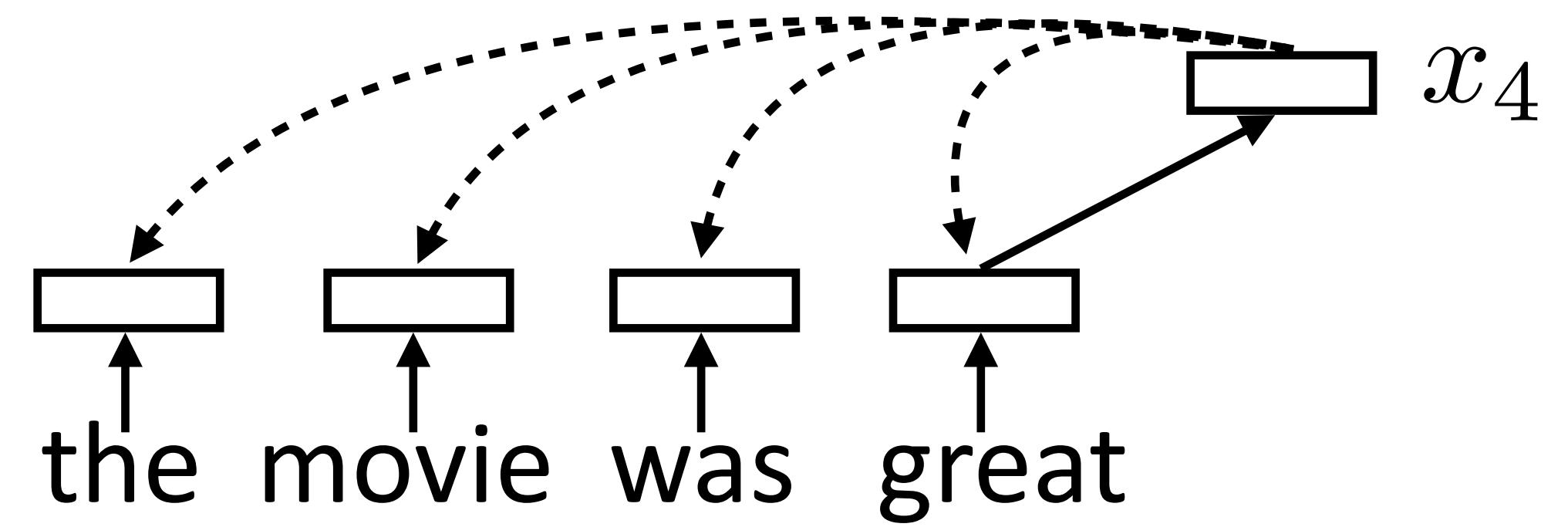
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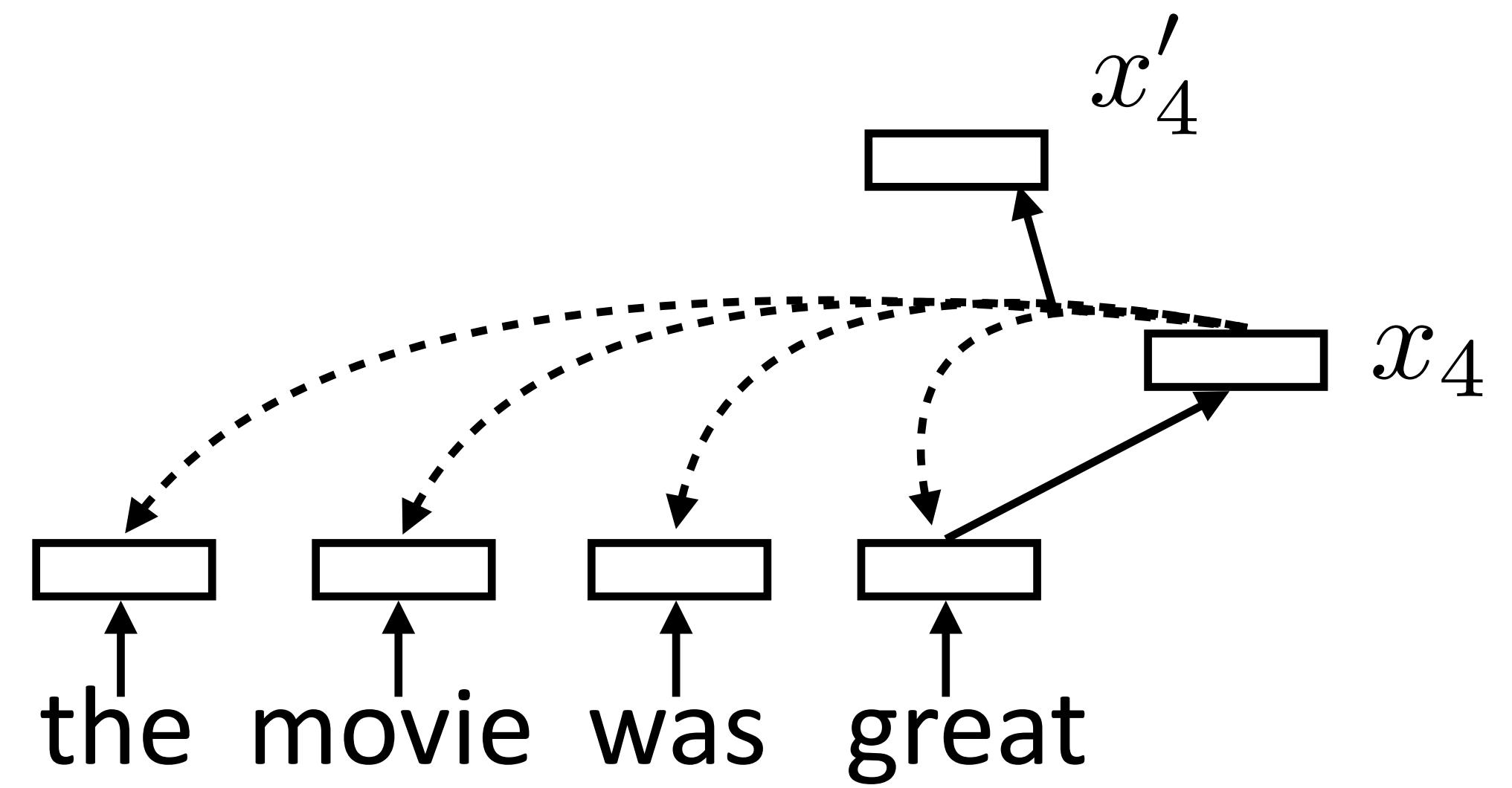
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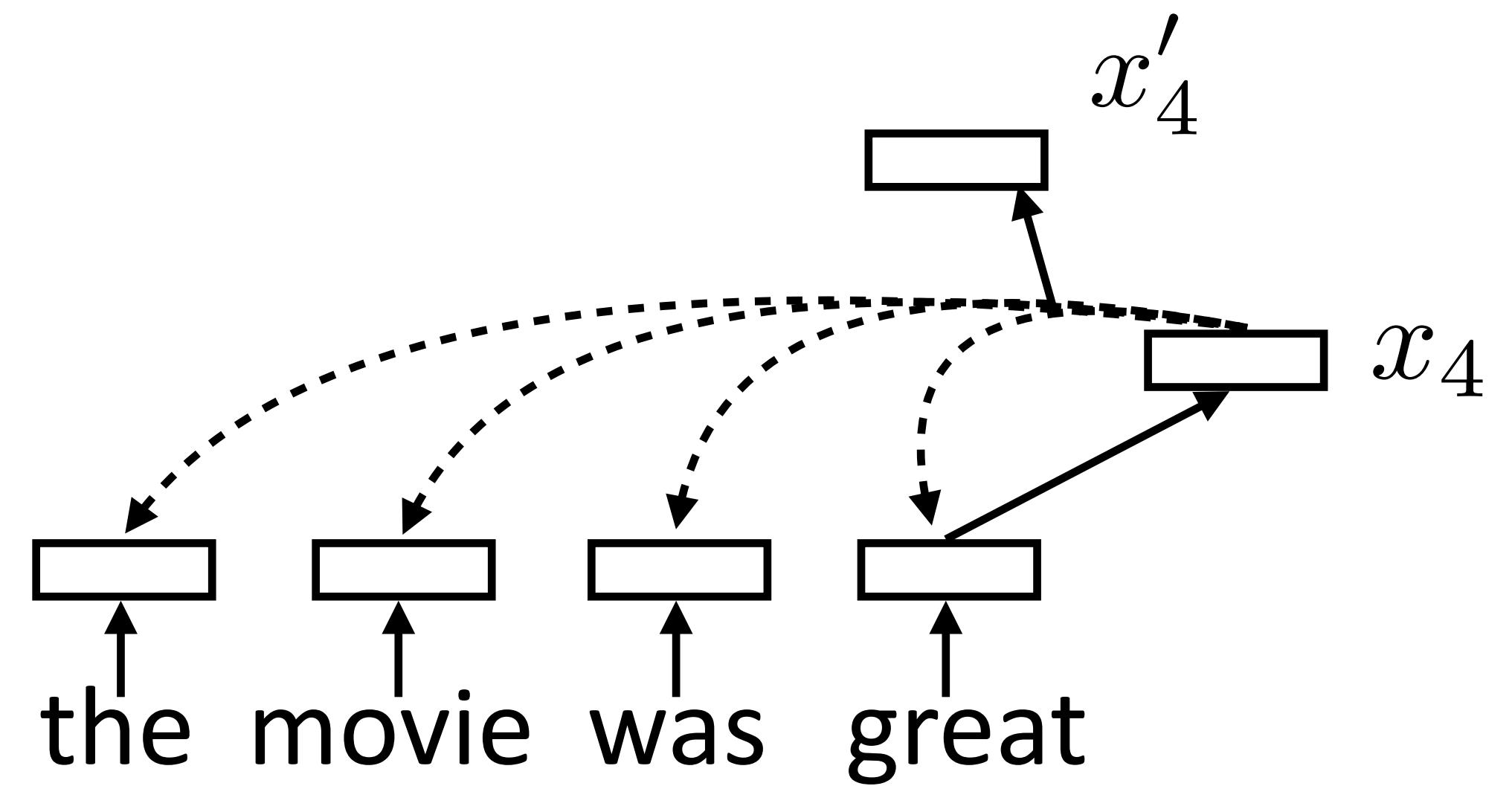
- ▶ Each word forms a “query” which then computes attention over each word



Self-Attention

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

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

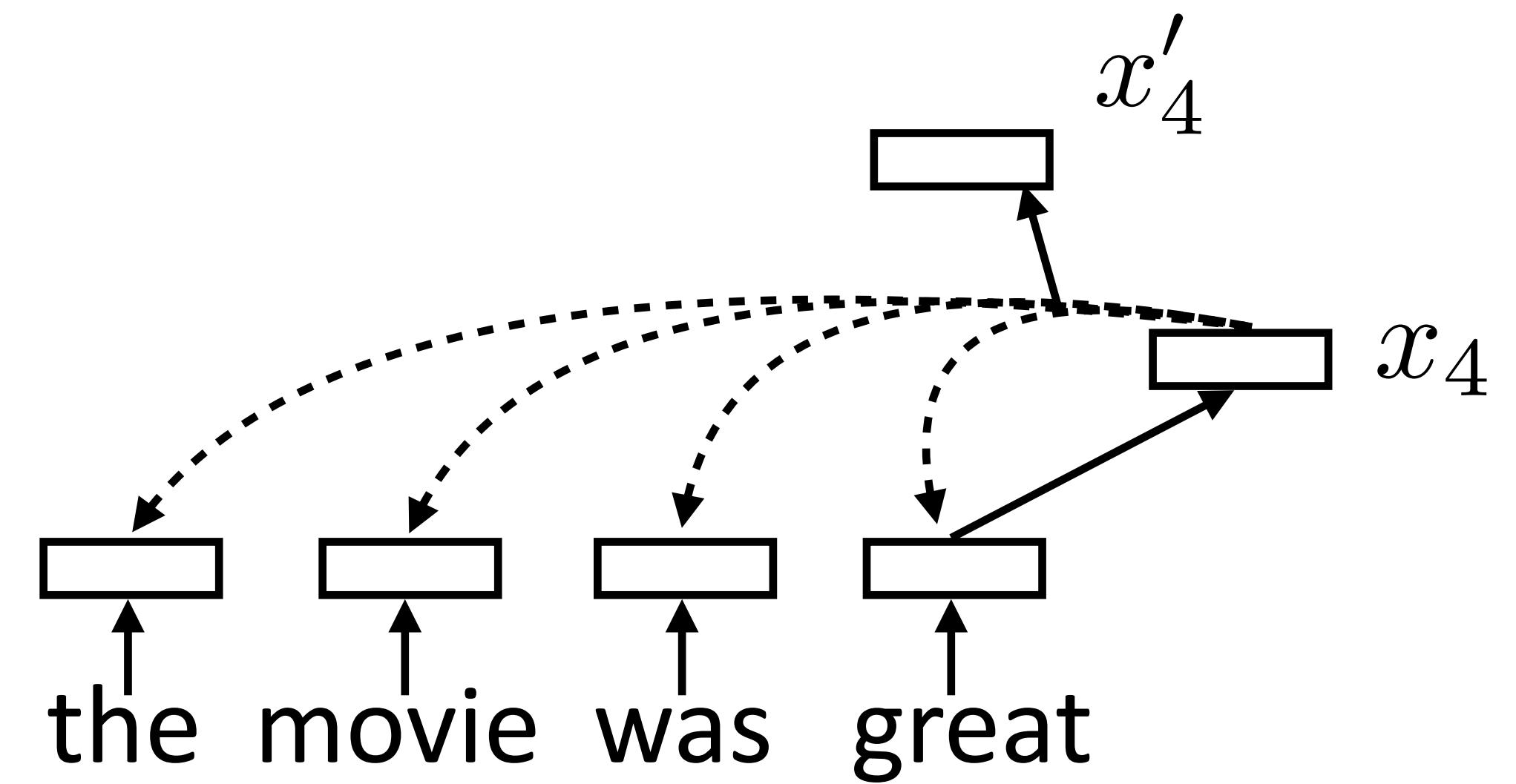


Self-Attention

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

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

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

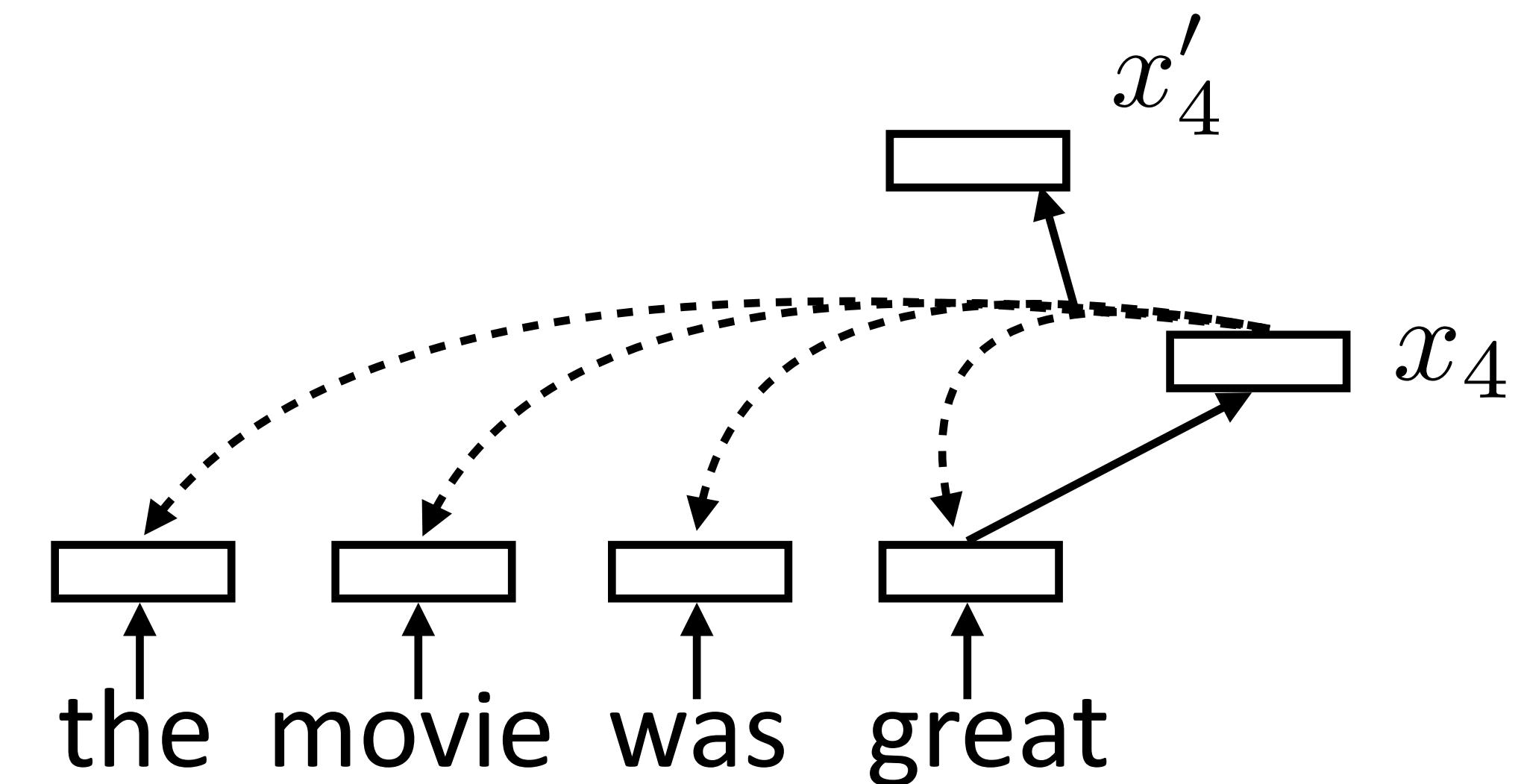


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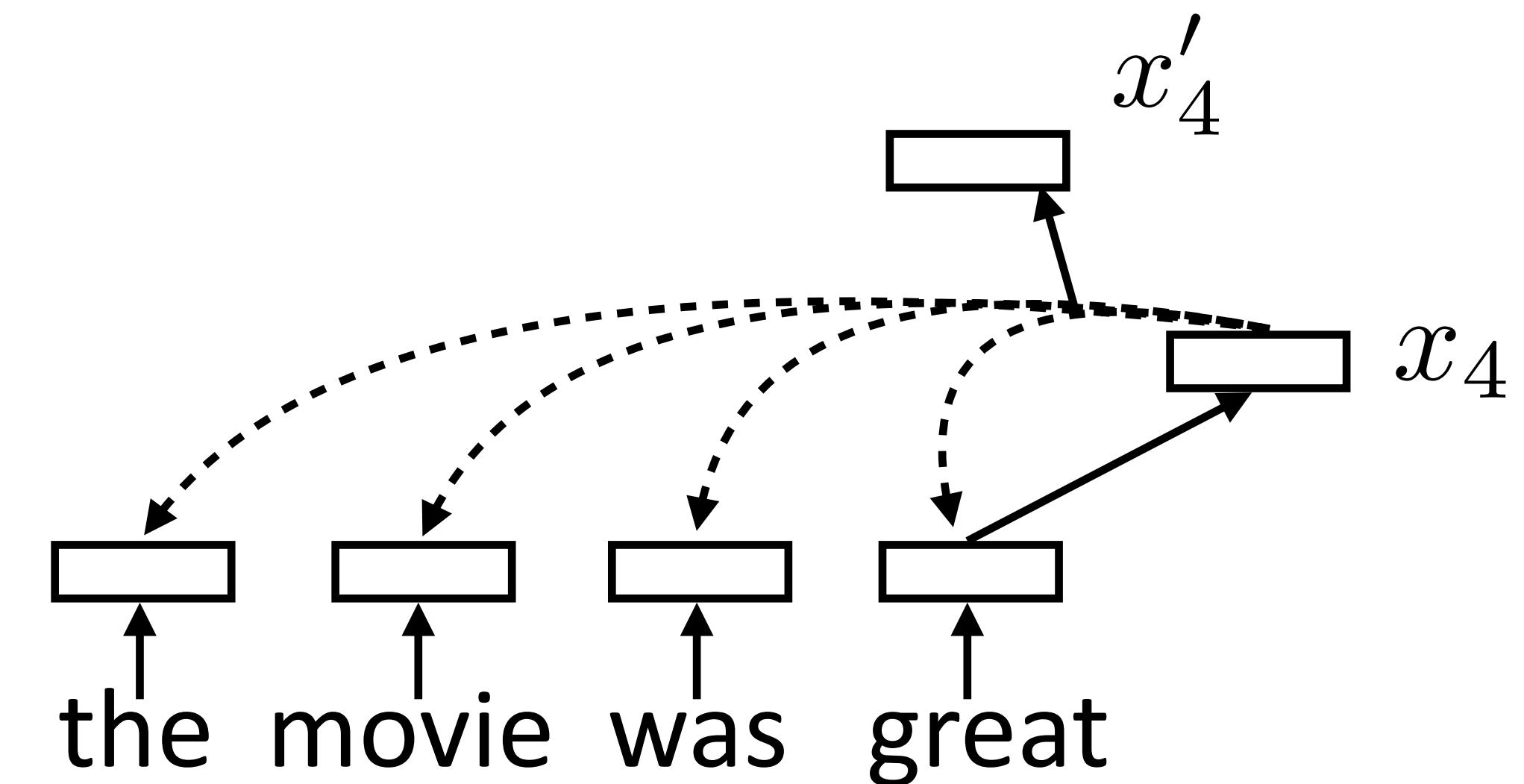
- ▶ Multiple “heads” analogous to different convolutional filters. Use parameters W_k and V_k to get different attention values + transform vectors

Self-Attention

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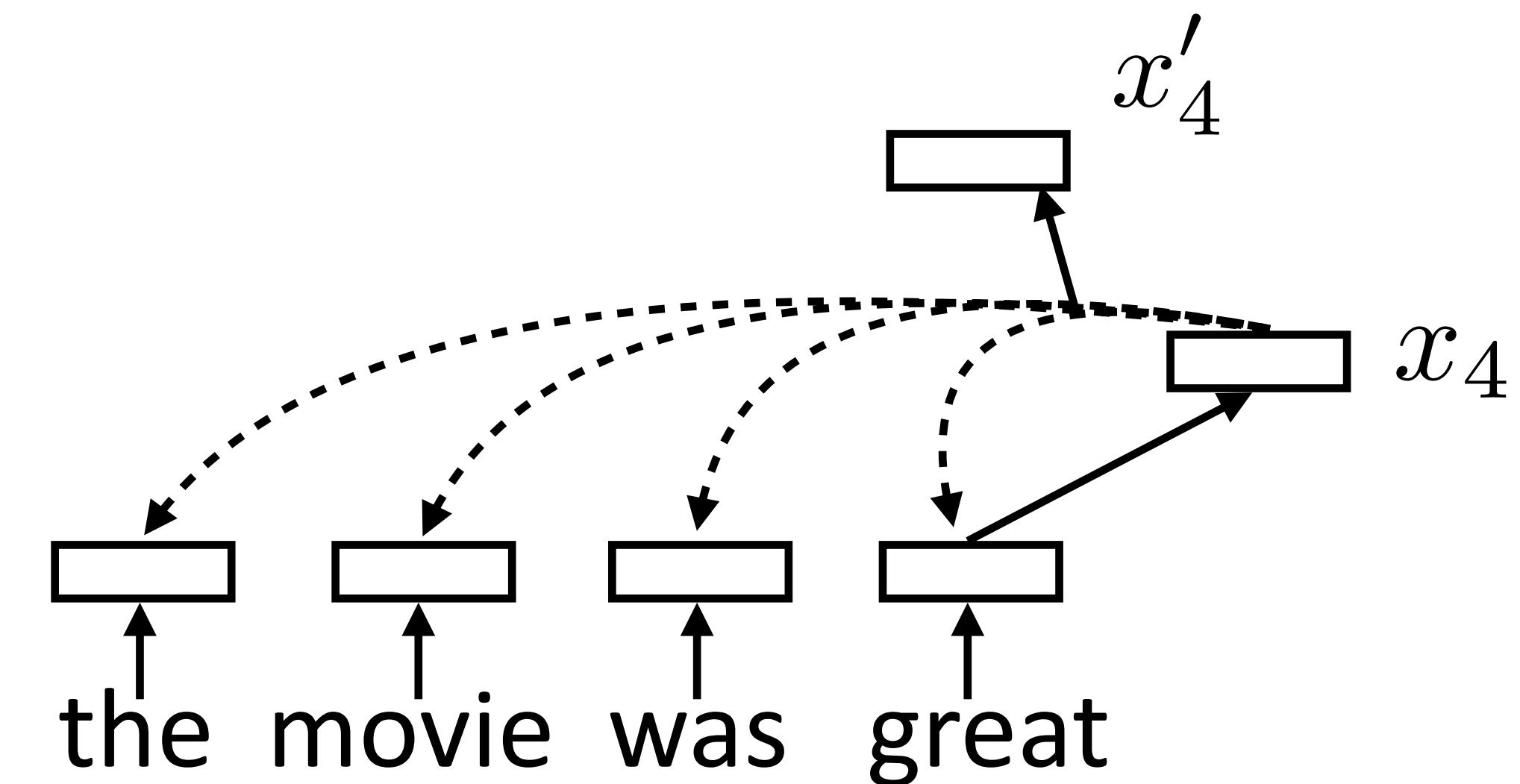
$$\alpha_{k,i,j} = \text{softmax}(x_i^\top W_k x_j)$$

Self-Attention

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

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

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



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

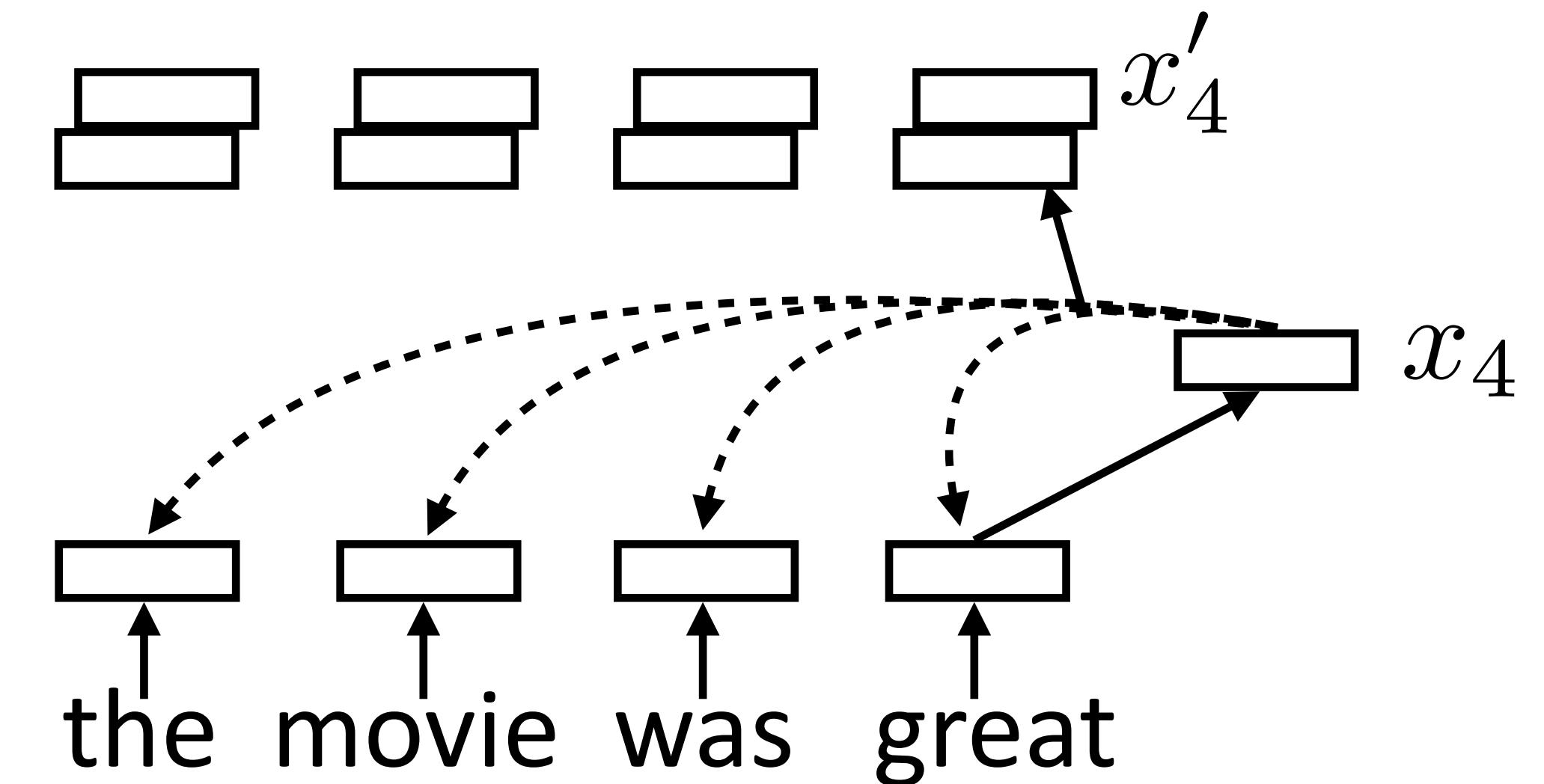
$$\alpha_{k,i,j} = \text{softmax}(x_i^\top W_k x_j) \quad x'_{k,i} = \sum_{j=1}^n \alpha_{k,i,j} V_k x_j$$

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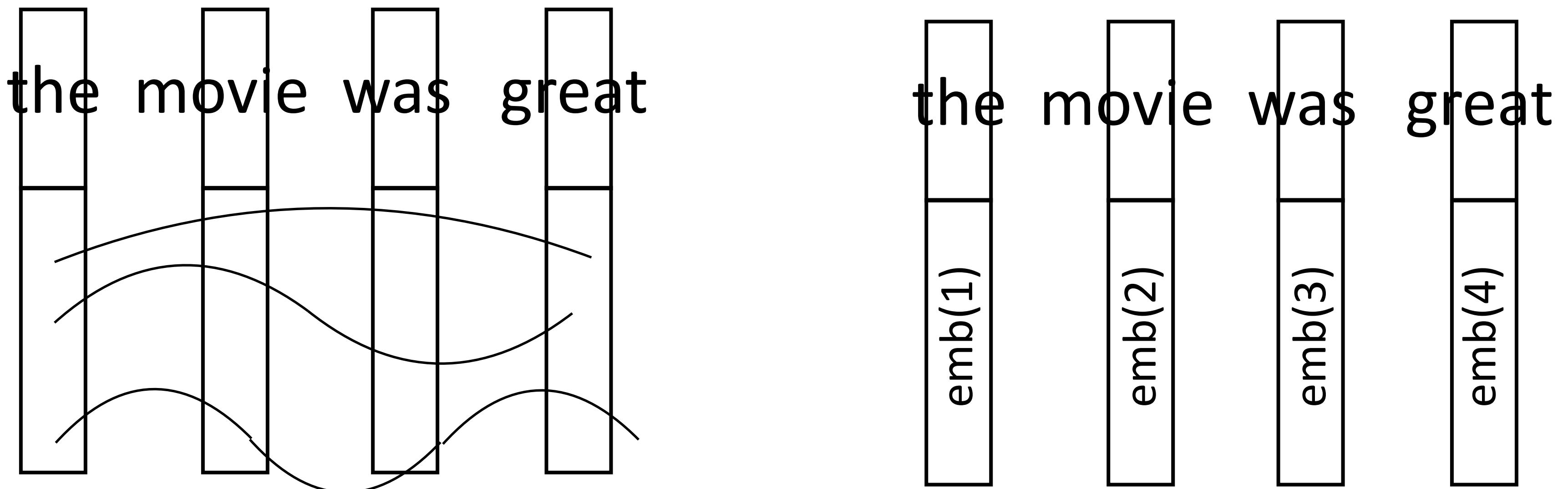
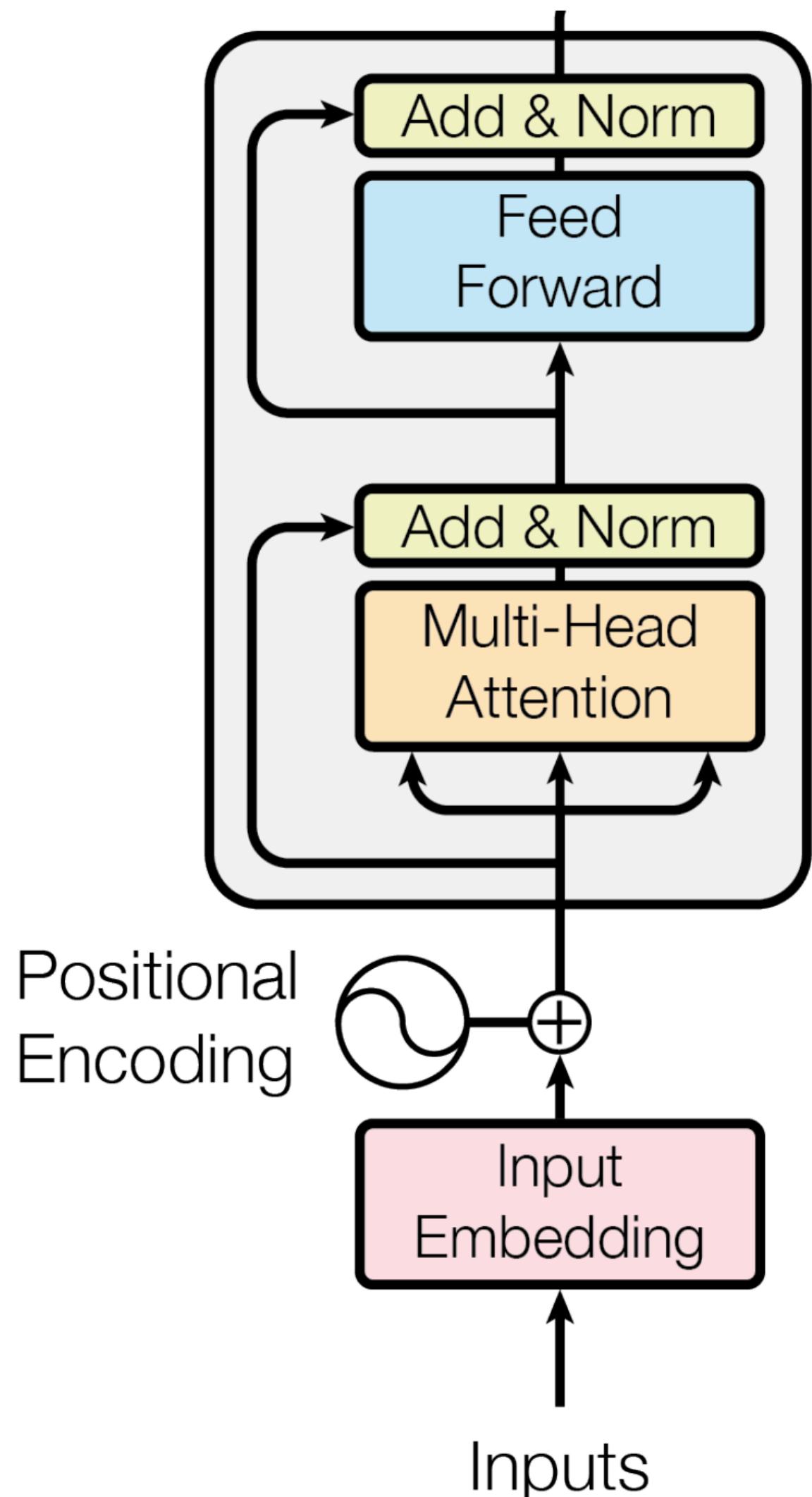
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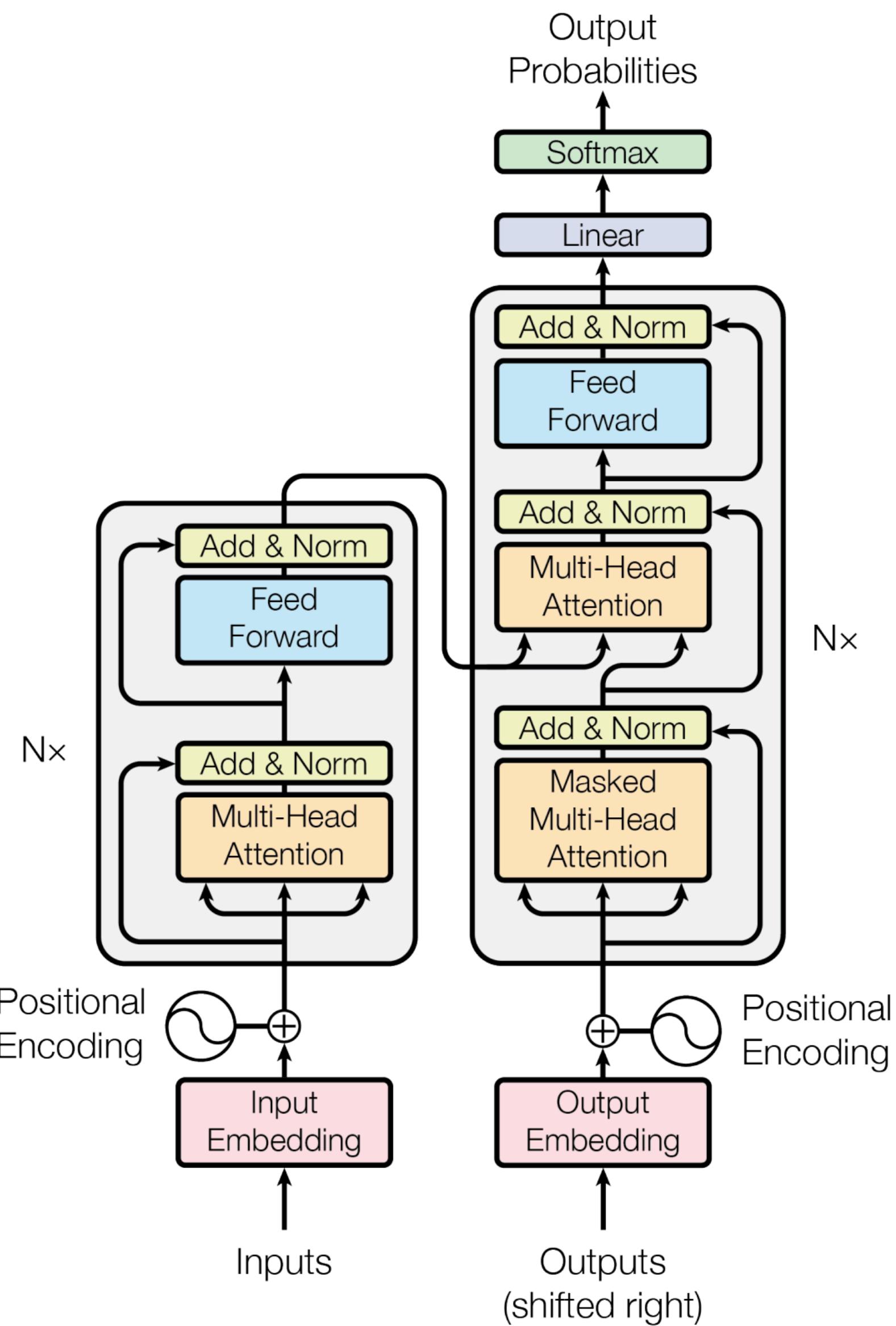
$$\alpha_{k,i,j} = \text{softmax}(x_i^\top W_k x_j) \quad x'_{k,i} = \sum_{j=1}^n \alpha_{k,i,j} V_k x_j$$

Transformers



- ▶ Augment word embedding with position embeddings, each dim is a sine/cosine wave of a different frequency. Closer points = higher dot products
- ▶ Works essentially as well as just encoding position as a one-hot vector

Transformers



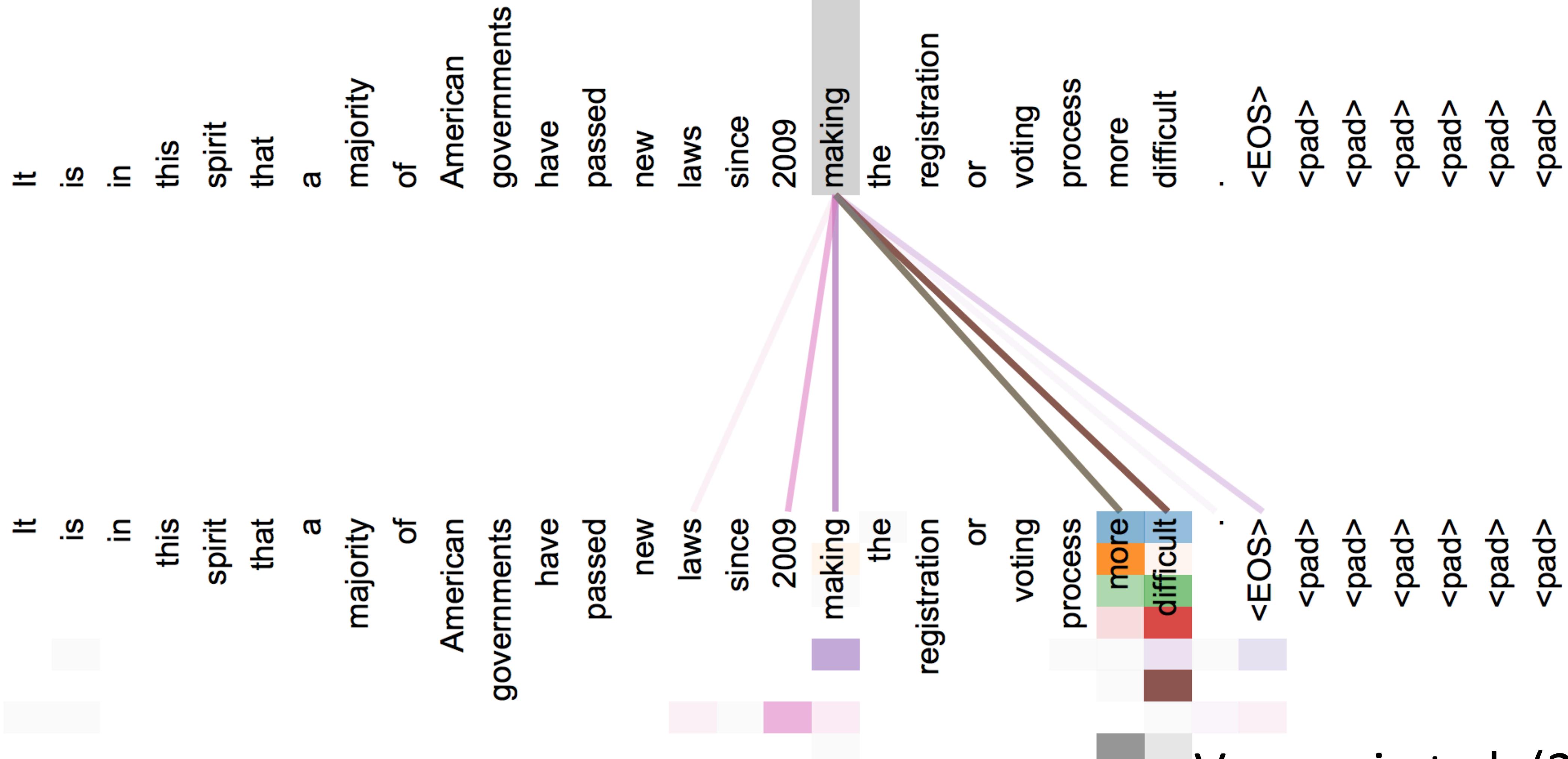
- ▶ Encoder and decoder are both transformers
- ▶ Decoder consumes the previous generated token (and attends to input), but has *no recurrent state*

Transformers

Model	BLEU	
	EN-DE	EN-FR
ByteNet [18]	23.75	
Deep-Att + PosUnk [39]		39.2
GNMT + RL [38]	24.6	39.92
ConvS2S [9]	25.16	40.46
MoE [32]	26.03	40.56
Deep-Att + PosUnk Ensemble [39]		40.4
GNMT + RL Ensemble [38]	26.30	41.16
ConvS2S Ensemble [9]	26.36	41.29
Transformer (base model)	27.3	38.1
Transformer (big)	28.4	41.8

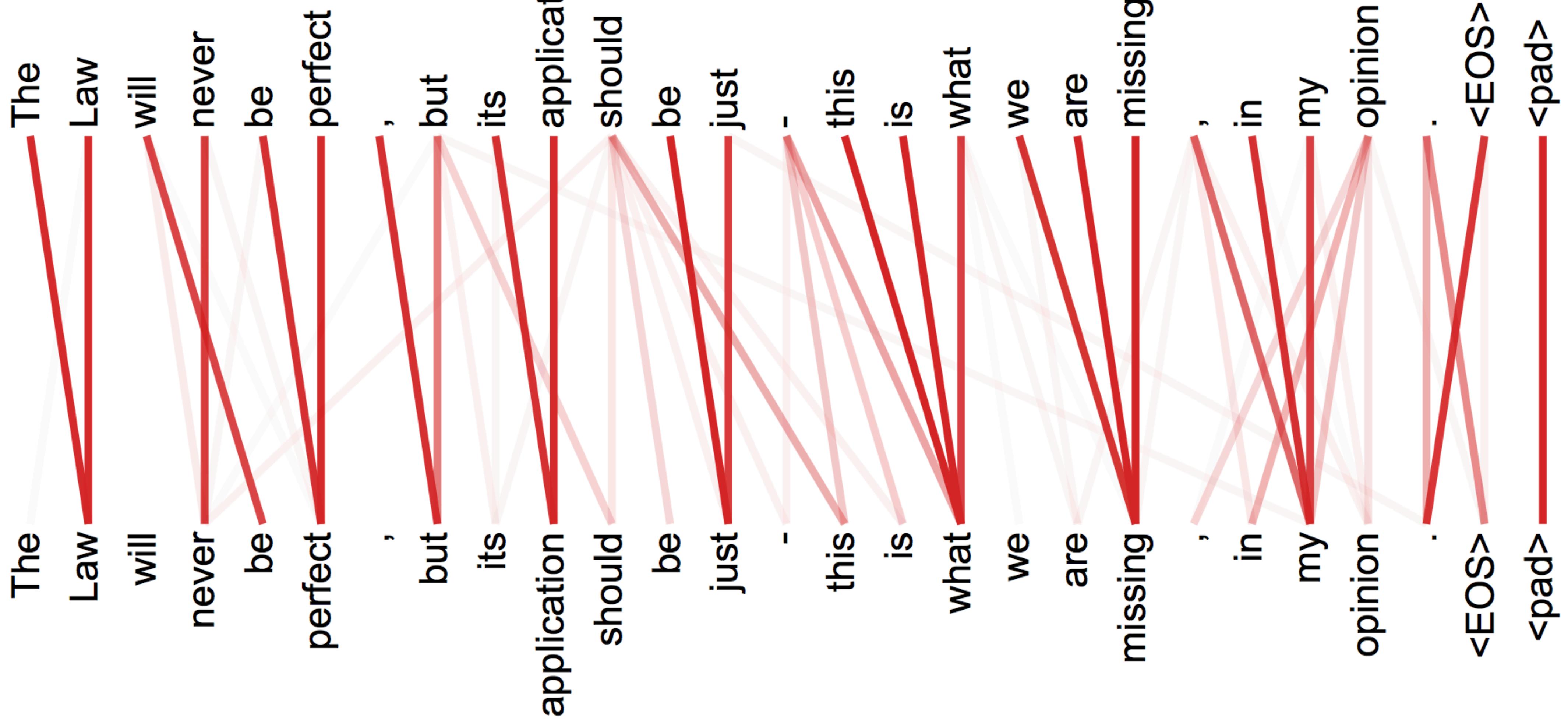
- ▶ Big = 6 layers, 1000 dim for each token, 16 heads,
base = 6 layers + other params halved

Visualization



Visualization

The Law will never be perfect , but its application should be just - this is what we are missing , in my opinion . <EOS> <pad>



Transformer Implementations

<https://nlp.seas.harvard.edu/2018/04/03/attention.html>



Members PI Code Publications

The Annotated Transformer

Apr 3, 2018

```
from IPython.display import Image  
Image(filename='images/aiayn.png')
```

Attention Is All You Need

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Transformer Implementations

<https://github.com/pytorch/fairseq>

README.md



license MIT release v0.10.2 build passing docs passing

Fairseq(-py) is a sequence modeling toolkit that allows researchers and developers to train custom models for translation, summarization, language modeling and other text generation tasks.

We provide reference implementations of various sequence modeling papers:

► [List of implemented papers](#)

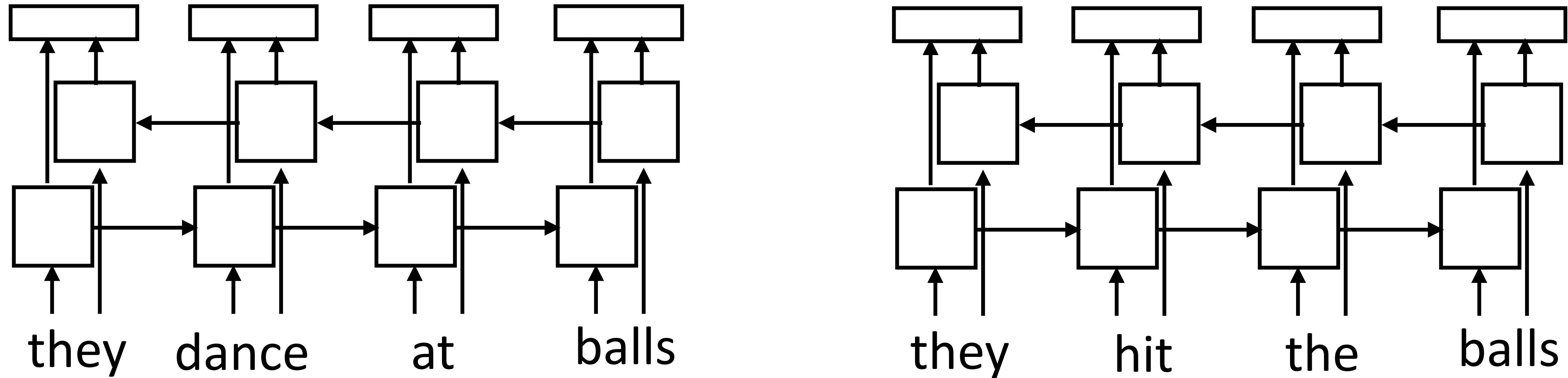
What's New:

- March 2021 [Added full parameter and optimizer state sharding + CPU offloading](#)
- February 2021 [Added LASER training code](#)
- December 2020: [Added Adaptive Attention Span code](#)
- December 2020: [GottBERT model and code released](#)
- November 2020: Adopted the [Hydra configuration framework](#)

Pretraining / ELMo

Recall: Context-dependent Embeddings

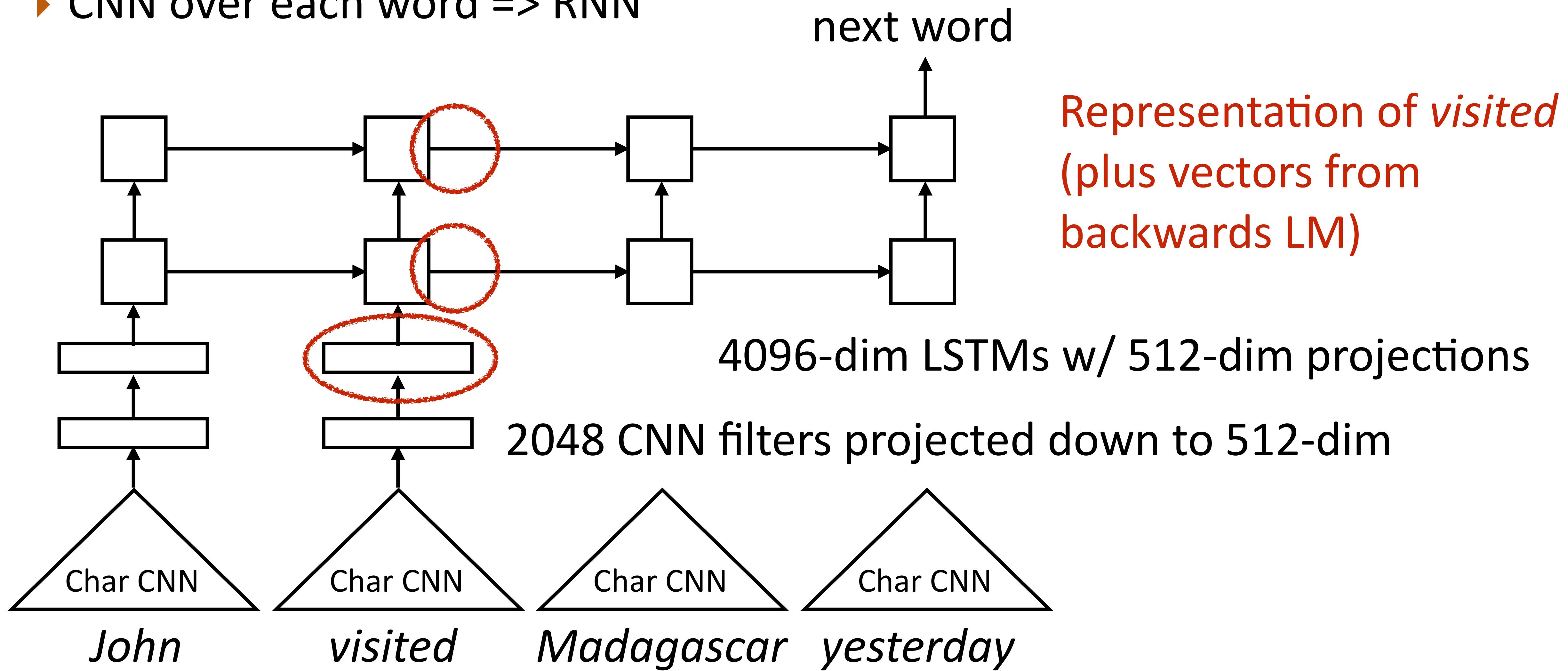
- ▶ How to handle different word senses? One vector for *balls*



- ▶ Train a neural language model to predict the next word given previous words in the sentence, use its internal representations as word vectors

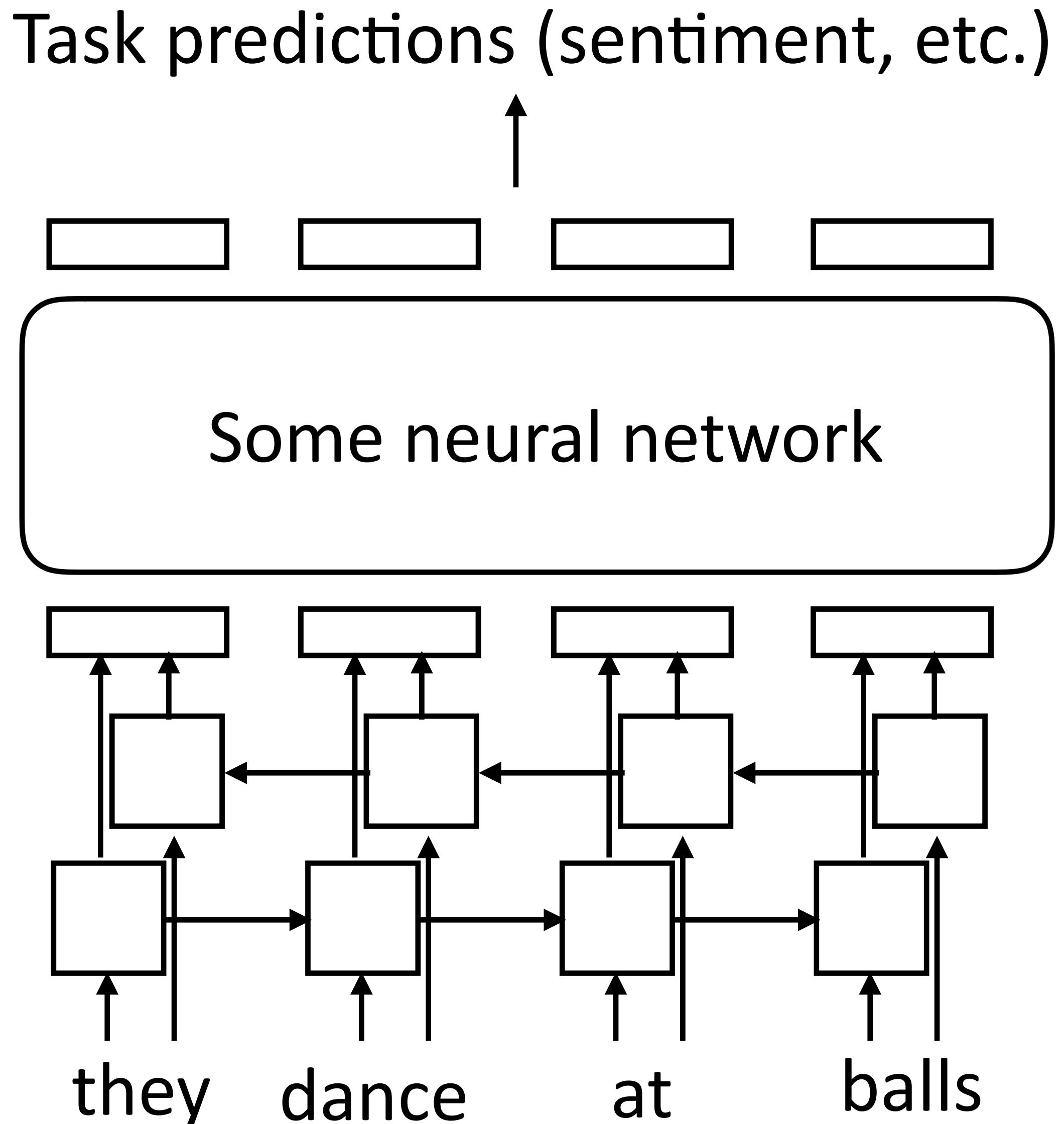
ELMo

- ▶ CNN over each word => RNN



How to apply ELMo?

- ▶ Take those embeddings and feed them into whatever architecture you want to use for your task
- ▶ *Frozen* embeddings: update the weights of your network but keep ELMo's parameters frozen
- ▶ *Fine-tuning*: backpropagate all the way into ELMo when training your model



Results: Frozen ELMo

Task	Previous SOTA		Our Baseline	ELMo + Baseline	Increase (Absolute/Relative)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

- ▶ Massive improvements across 5 benchmark datasets: question answering, natural language inference, semantic role labeling (discussed later in the course), coreference resolution, named entity recognition, and sentiment analysis

How to apply ELMo?

Pretraining	Adaptation	NER	SA	Nat. lang. inference		Semantic textual similarity		
		CoNLL 2003	SST-2	MNLI	SICK-E	SICK-R	MRPC	STS-B
Skip-thoughts	❄️	-	81.8	62.9	-	86.6	75.8	71.8
ELMo	❄️	91.7	91.8	79.6	86.3	86.1	76.0	75.9
	🔥	91.9	91.2	76.4	83.3	83.3	74.7	75.5
	Δ=🔥-❄️	0.2	-0.6	-3.2	-3.3	-2.8	-1.3	-0.4

- ▶ How does frozen (❄️) vs. fine-tuned (🔥) compare?

- ▶ Recommendations:

Conditions			Guidelines
Pretrain	Adapt.	Task	
Any	❄️	Any	Add many task parameters
Any	🔥	Any	Add minimal task parameters ⚠ Hyper-parameters
Any	Any	Seq. / clas.	❄️ and 🔥 have similar performance
ELMo	Any	Sent. pair	use ❄️
BERT	Any	Sent. pair	use 🔥

Why is language modeling a good objective?

- ▶ “Impossible” problem but bigger models seem to do better and better at distributional modeling (no upper limit yet)
- ▶ Successfully predicting next words requires modeling lots of different effects in text

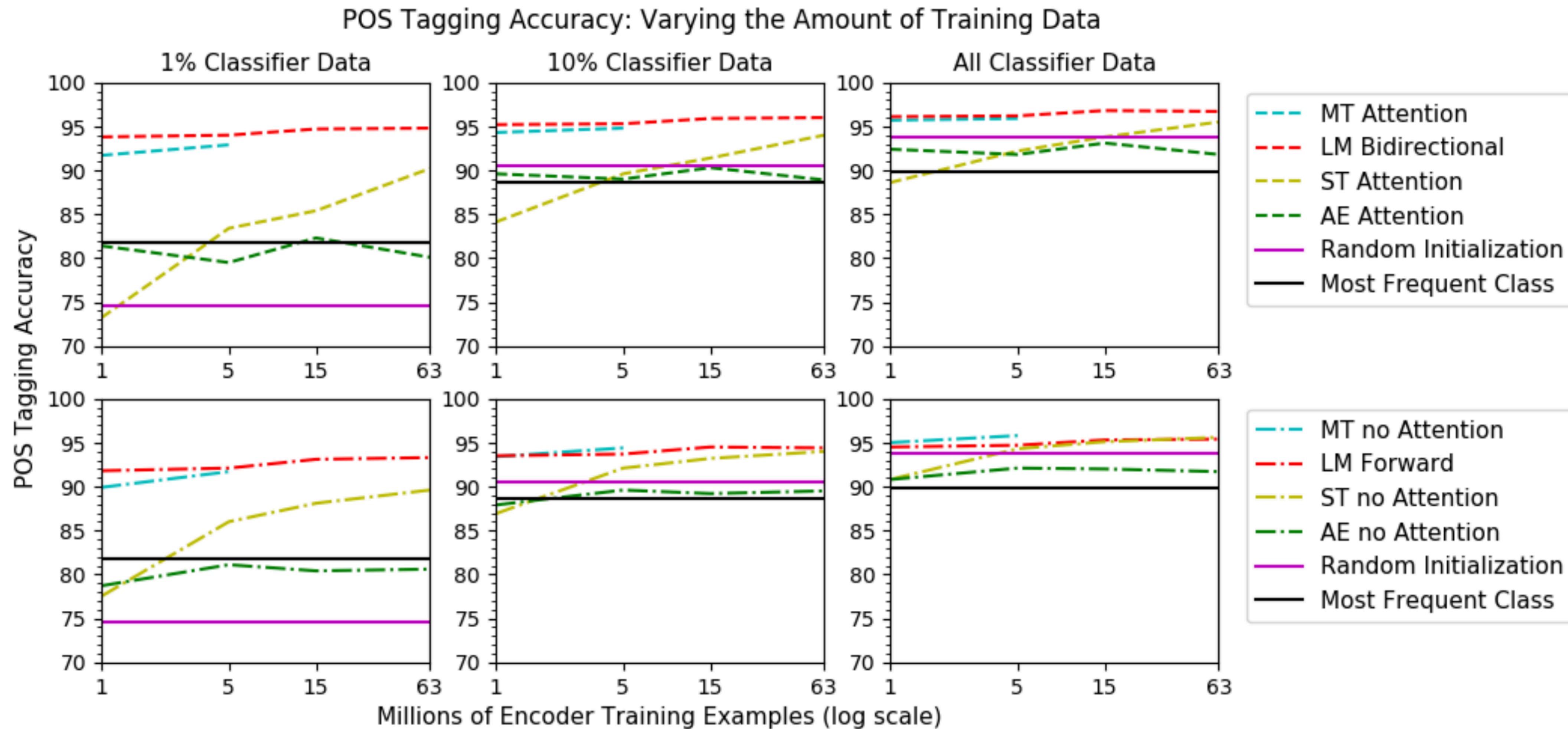
Context: My wife refused to allow me to come to Hong Kong when the plague was at its height and –” “Your wife, Johanne? You are married at last ?” Johanne grinned. “Well, when a man gets to my age, he starts to need a few home comforts.

Target sentence: After my dear mother passed away ten years ago now, I became _____.

Target word: lonely

- ▶ LAMBADA dataset (Papernot et al., 2016): explicitly targets world knowledge and very challenging LM examples
- ▶ Coreference, Winograd schema, and much more

Why is language modeling a good objective?



Zhang and Bowman (2018)

Why did this take time to catch on?

- ▶ Earlier version of ELMo by the same authors in 2017, but it was only evaluated on tagging tasks, gains were 1% or less
- ▶ Required: training on lots of data, having the right architecture, significant hyperparameter tuning

Probing ELMo

- ▶ From each layer of the ELMo model, attempt to predict something: POS tags, word senses, etc.
- ▶ Higher accuracy => ELMo is capturing that thing more nicely

Model	F ₁
WordNet 1st Sense Baseline	65.9
Raganato et al. (2017a)	69.9
Iacobacci et al. (2016)	70.1
CoVe, First Layer	59.4
CoVe, Second Layer	64.7
biLM, First layer	67.4
biLM, Second layer	69.0

Table 5: All-words fine grained WSD F₁. For CoVe and the biLM, we report scores for both the first and second layer biLSTMs.

Model	Acc.
Collobert et al. (2011)	97.3
Ma and Hovy (2016)	97.6
Ling et al. (2015)	97.8
CoVe, First Layer	93.3
CoVe, Second Layer	92.8
biLM, First Layer	97.3
biLM, Second Layer	96.8

Table 6: Test set POS tagging accuracies for PTB. For CoVe and the biLM, we report scores for both the first and second layer biLSTMs.

BERT

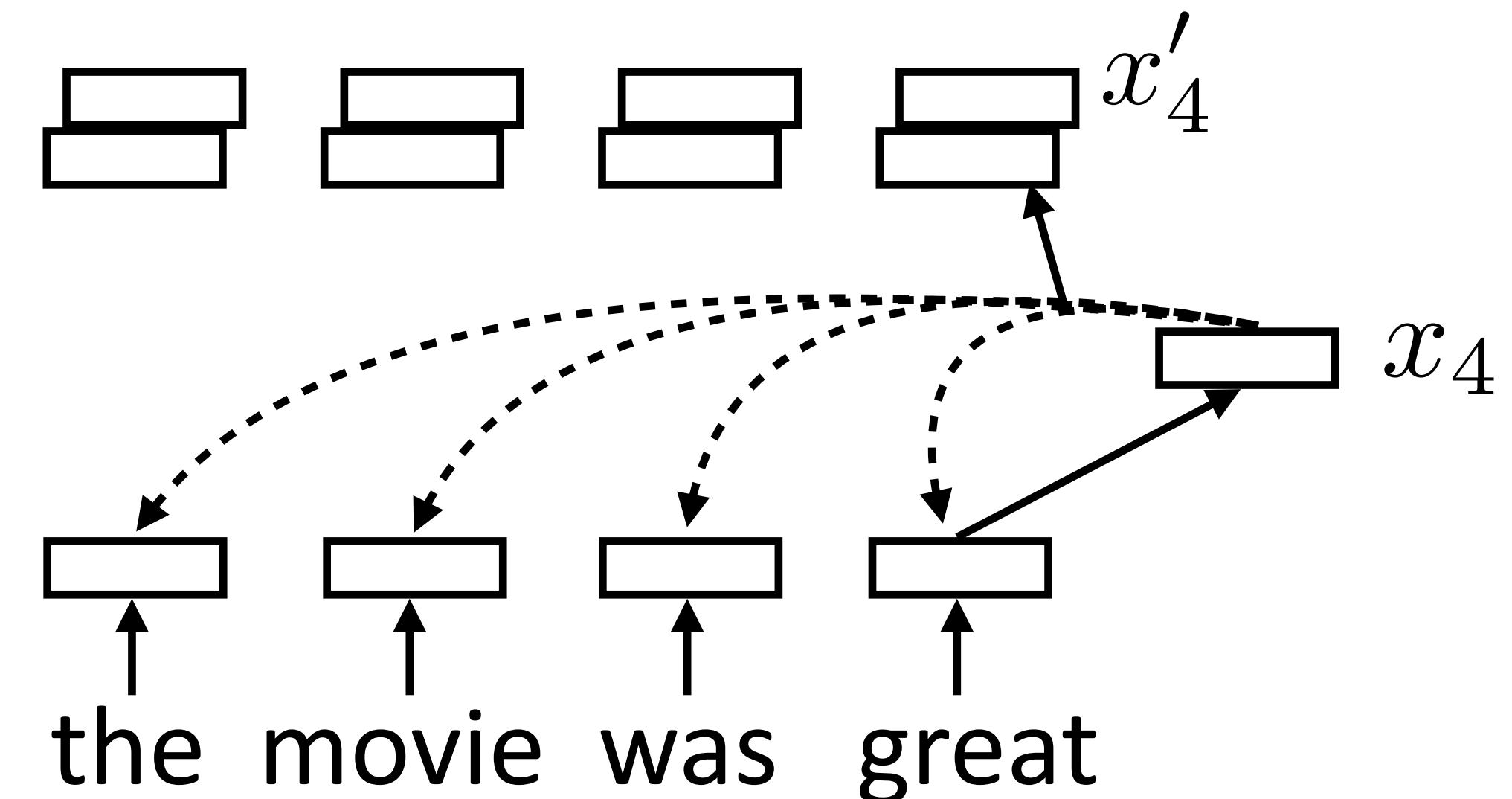


Recall: Self-Attention

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

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

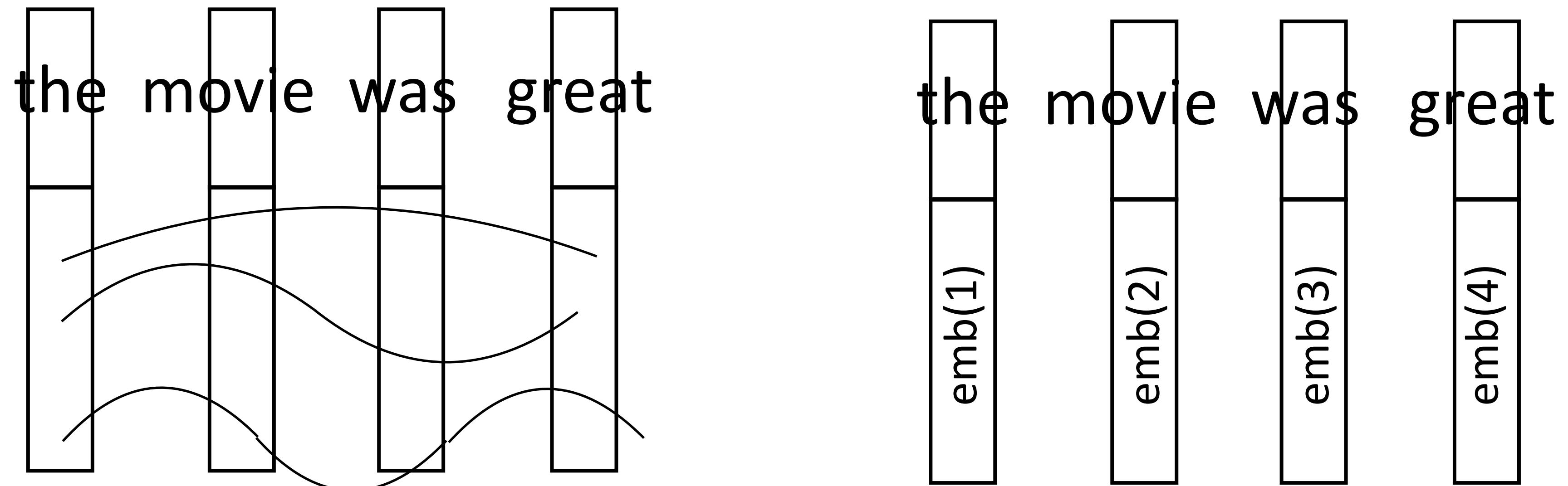
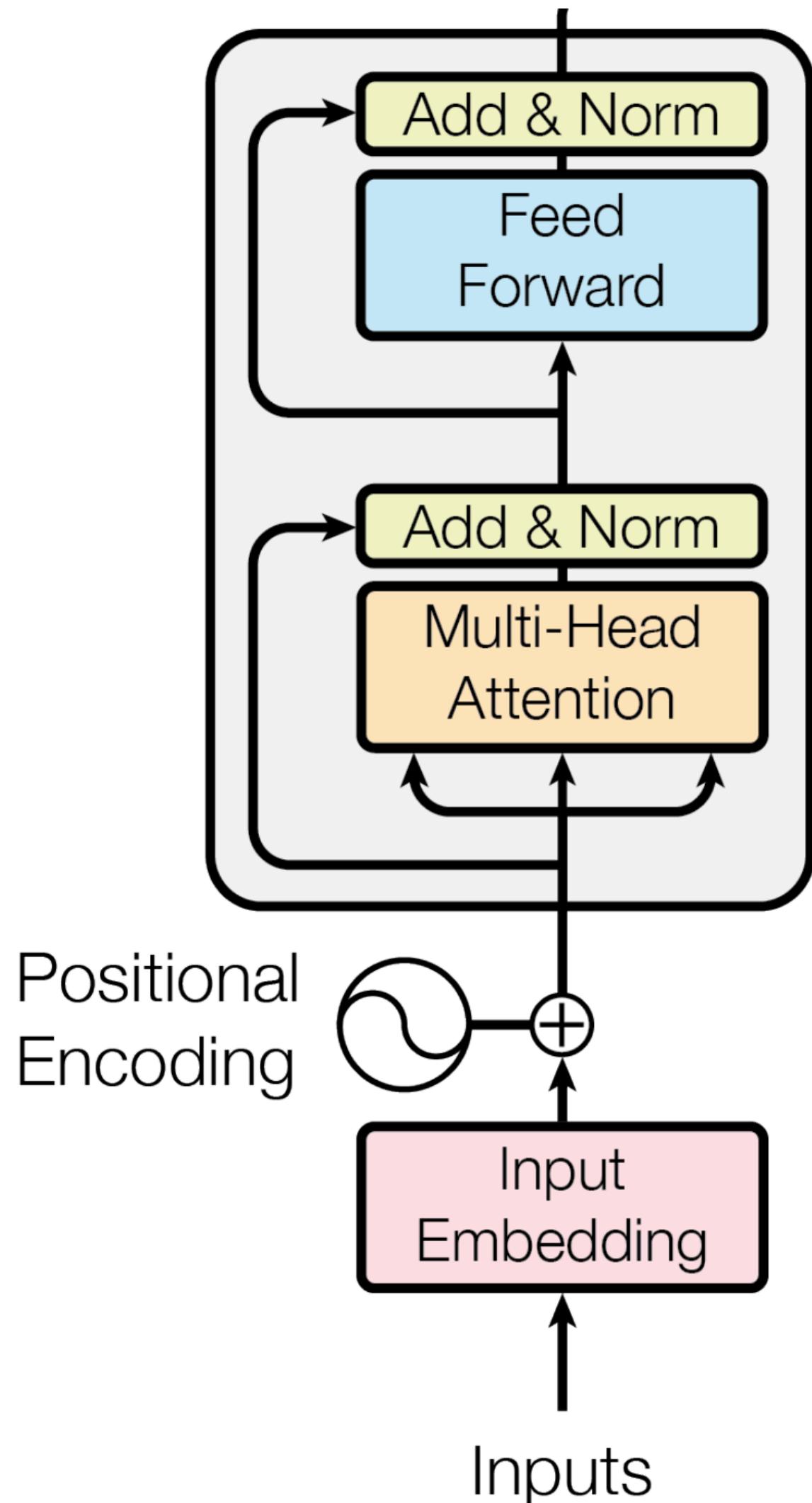
$$x'_i = \sum_{j=1}^n \alpha_{i,j} x_j \quad \text{vector} = \text{sum of scalar} * \text{vector}$$



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

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

Recall: Transformers



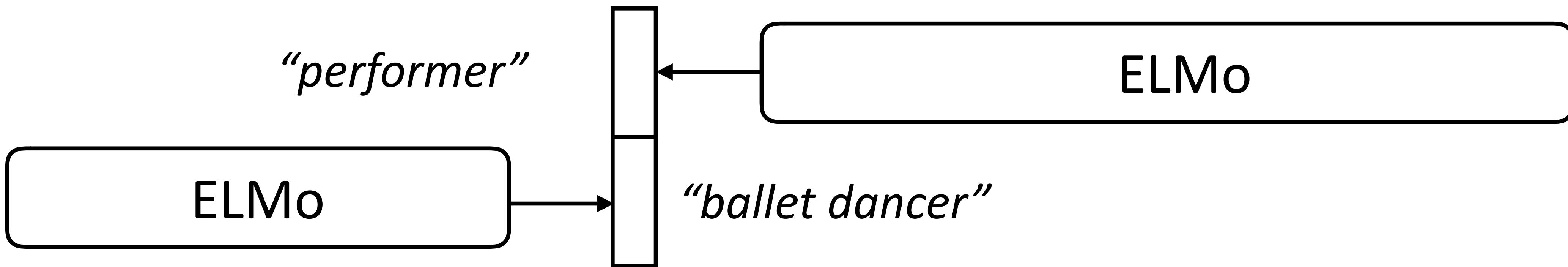
- ▶ Augment word embedding with position embeddings, each dim is a sine/cosine wave of a different frequency. Closer points = higher dot products
- ▶ Works essentially as well as just encoding position as a one-hot vector

BERT

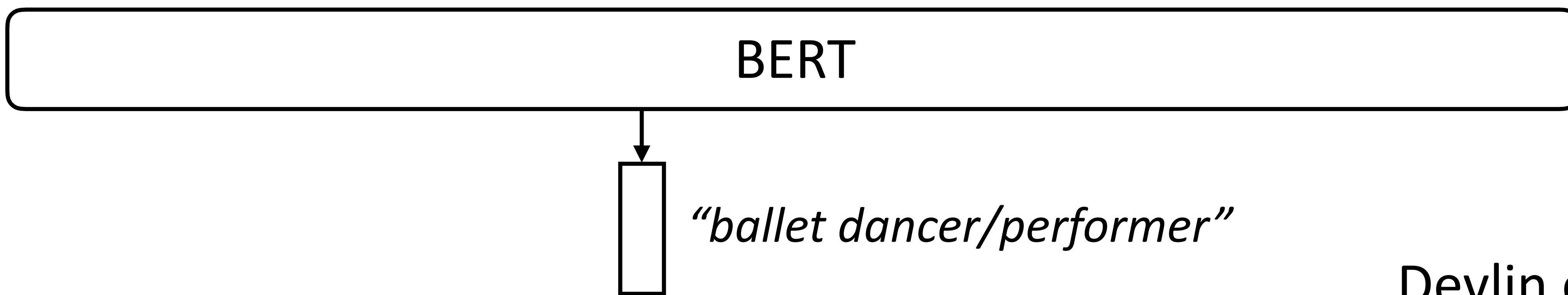
- ▶ AI2 made ELMo in spring 2018, GPT was released in summer 2018, BERT came out October 2018
- ▶ Three major changes compared to ELMo:
 - ▶ Transformers instead of LSTMs (transformers in GPT as well)
 - ▶ Bidirectional <=> Masked LM objective instead of standard LM
 - ▶ Fine-tune instead of freeze at test time

BERT

- ▶ ELMo is a unidirectional model (as is GPT): we can concatenate two unidirectional models, but is this the right thing to do?
- ▶ ELMo reprs look at each direction in isolation; BERT looks at them jointly

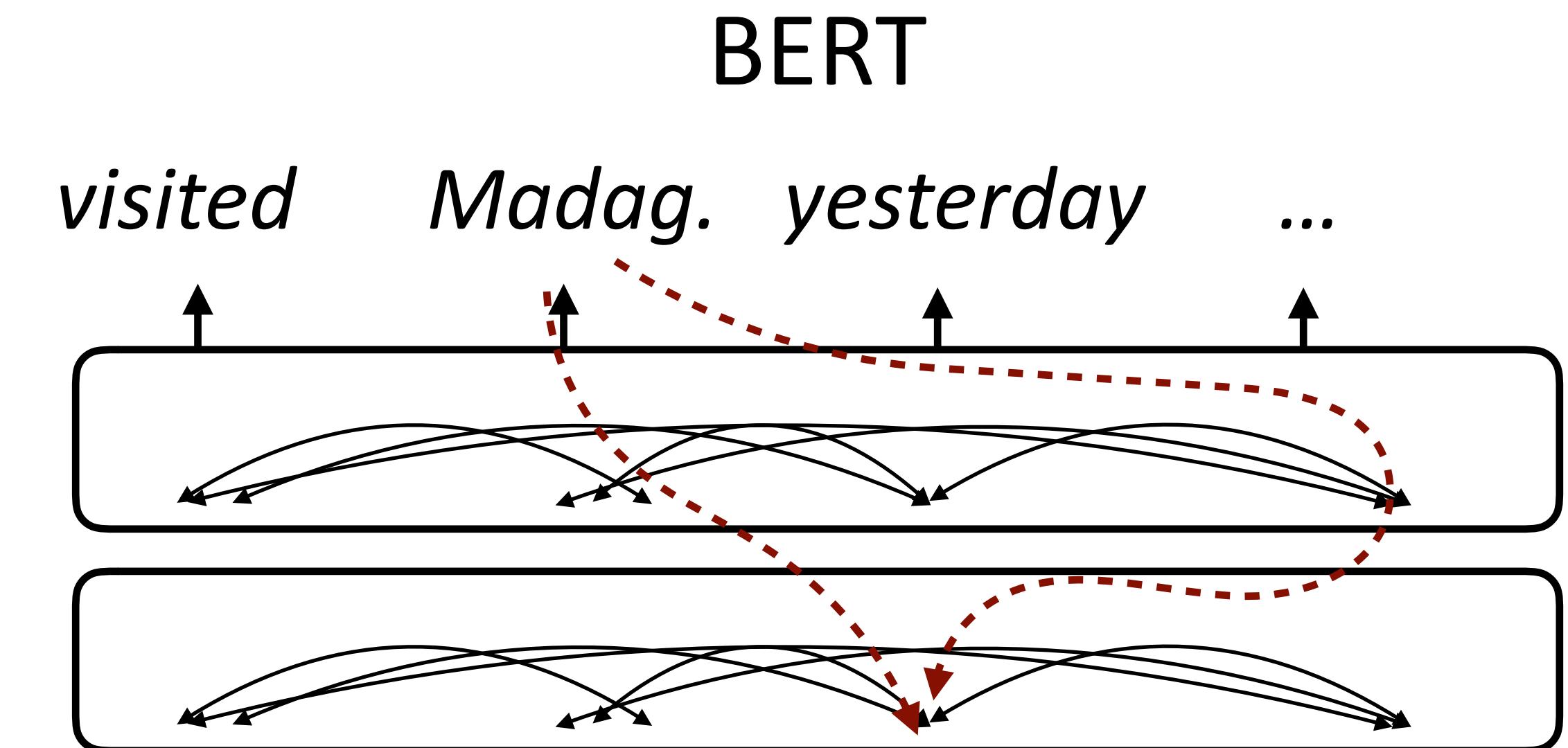
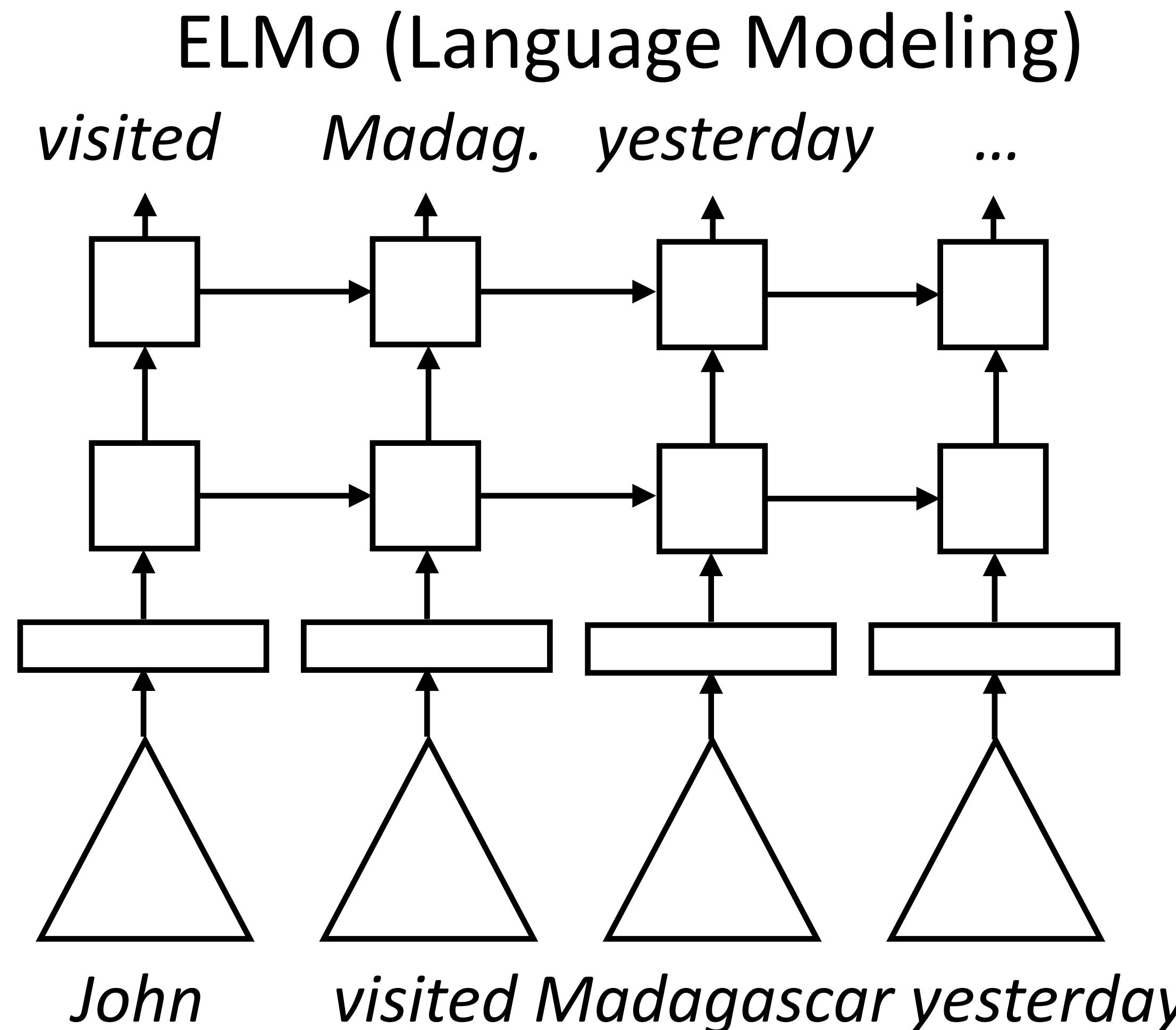


A stunning ballet dancer, Copeland is one of the best performers to see live.



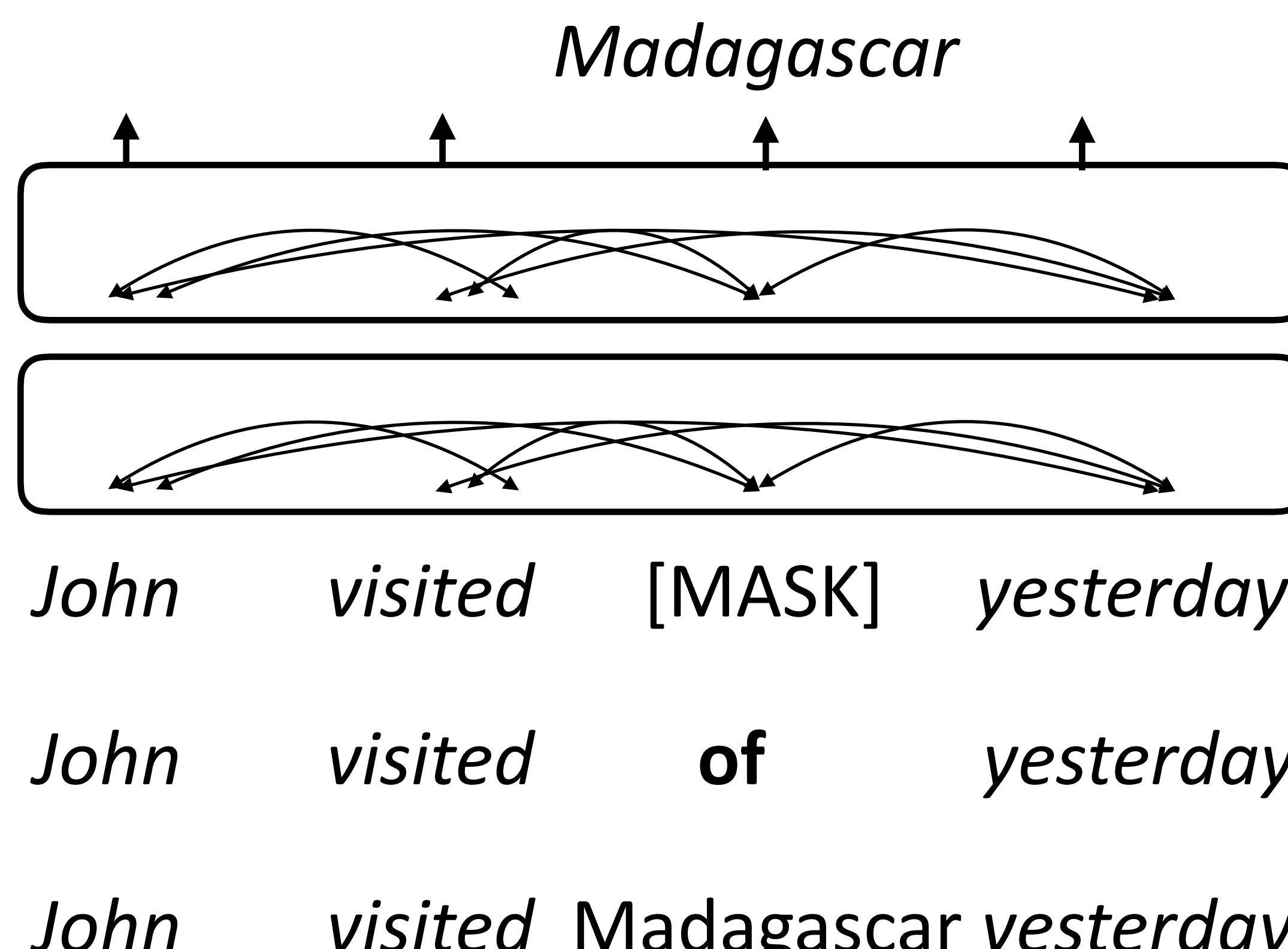
BERT

- ▶ How to learn a “deeply bidirectional” model? What happens if we just replace an LSTM with a transformer?



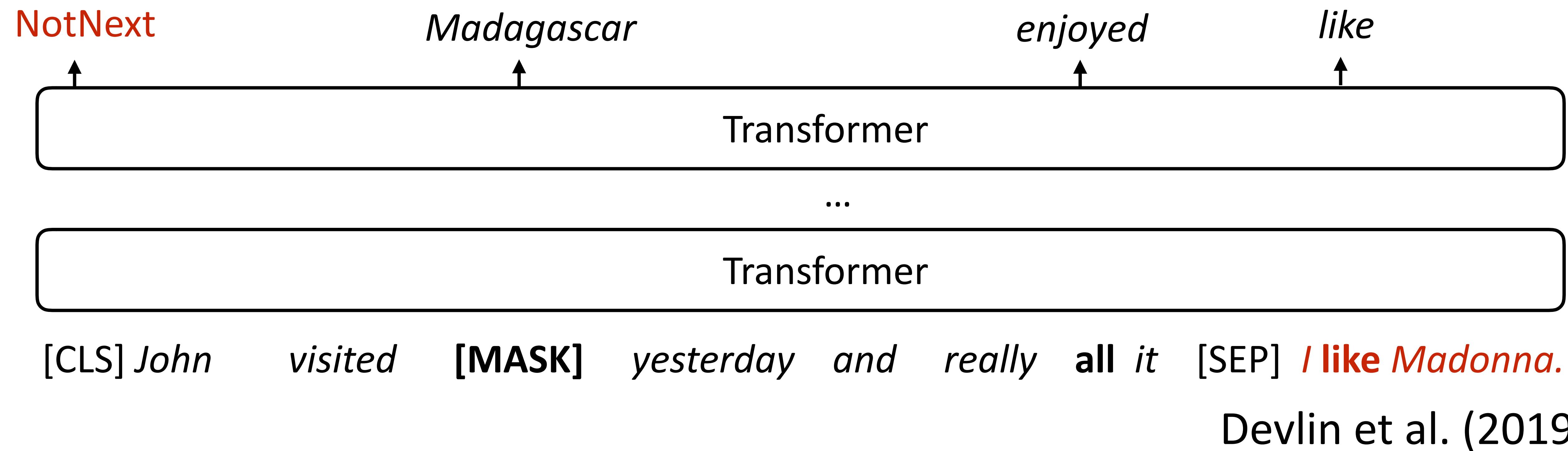
- John visited Madagascar yesterday*
- ▶ Transformer LMs have to be “one-sided” (only attend to previous tokens), not what we want

Masked Language Modeling

- ▶ How to prevent cheating? Next word prediction fundamentally doesn't work for bidirectional models, instead do *masked language modeling*
 - ▶ BERT formula: take a chunk of text, predict 15% of the tokens
 - ▶ For 80% (of the 15%), replace the input token with [MASK]
 - ▶ For 10%, replace w/random
 - ▶ For 10%, keep same
- 
- Madagascar
- John visited [MASK] yesterday
- John visited of yesterday
- John visited Madagascar yesterday

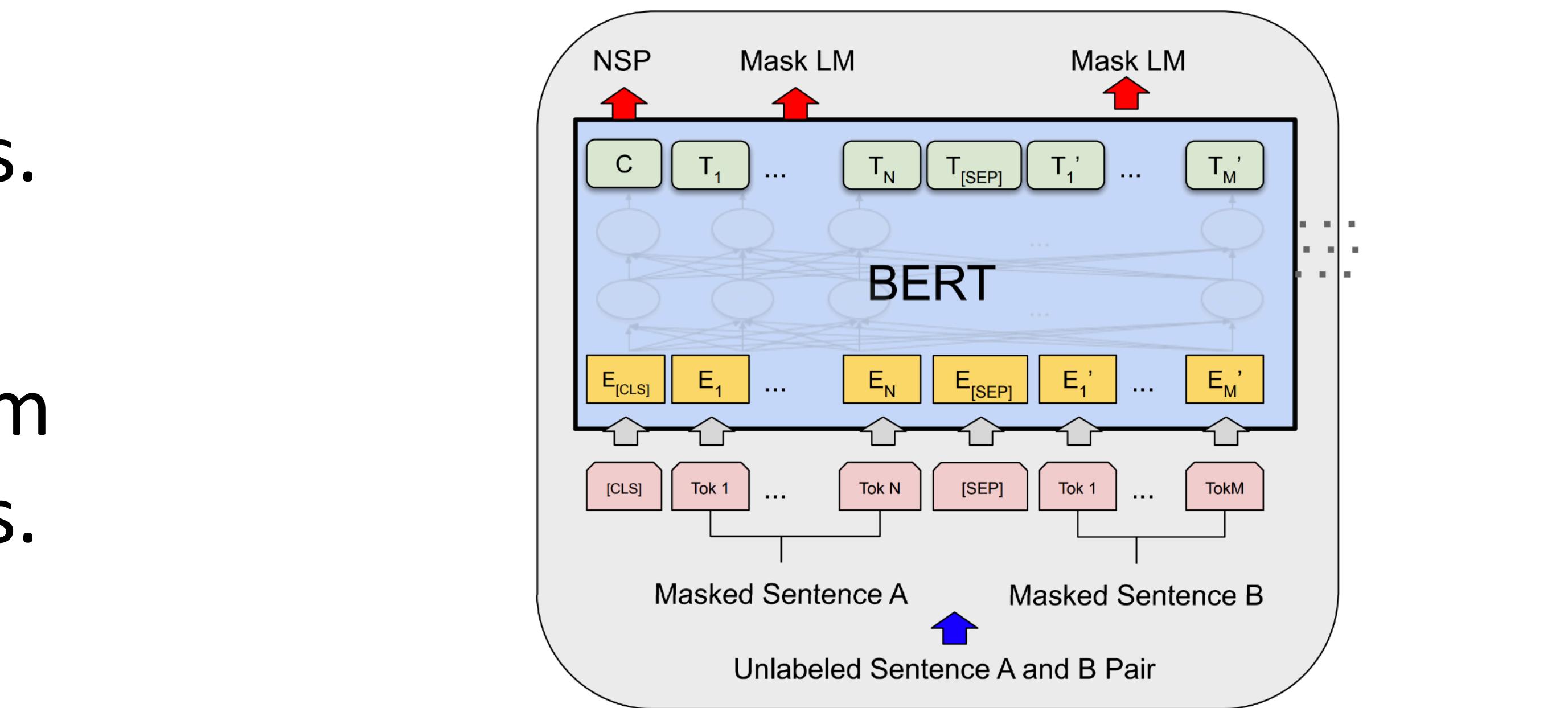
Next “Sentence” Prediction

- ▶ Input: [CLS] Text chunk 1 [SEP] Text chunk 2
- ▶ 50% of the time, take the true next chunk of text, 50% of the time take a random other chunk. Predict whether the next chunk is the “true” next
- ▶ BERT objective: masked LM + next sentence prediction

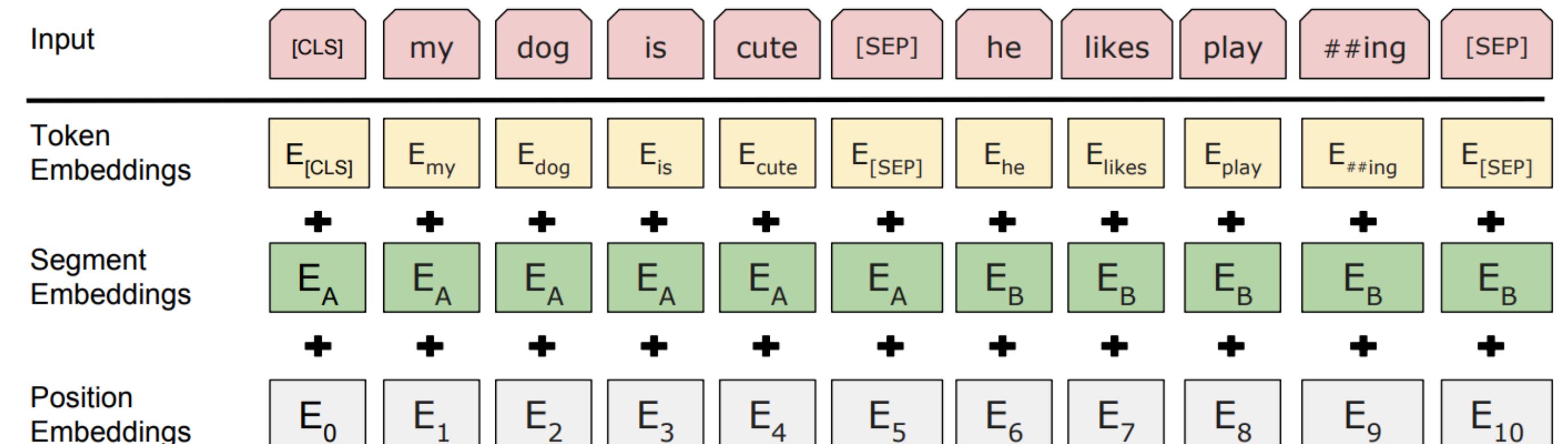


BERT Architecture

- ▶ BERT Base: 12 layers, 768-dim per wordpiece token, 12 heads.
Total params = 110M
- ▶ BERT Large: 24 layers, 1024-dim per wordpiece token, 16 heads.
Total params = 340M

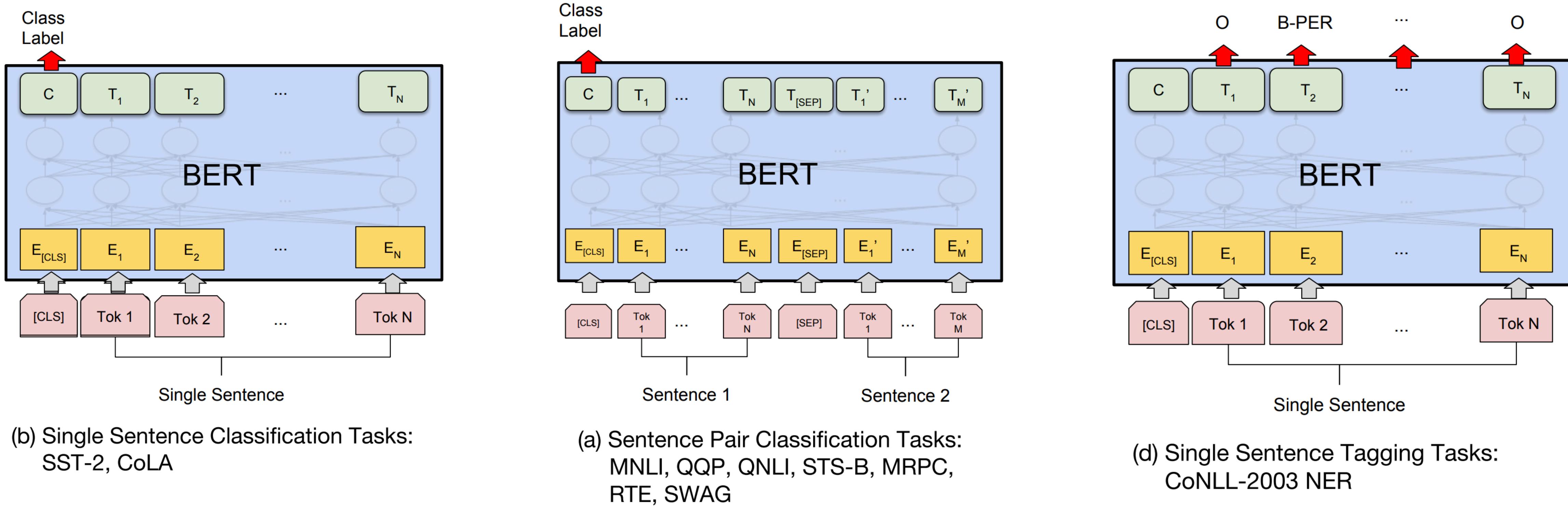


- ▶ Positional embeddings and segment embeddings, 30k word pieces



- ▶ This is the model that gets pre-trained on a large corpus

What can BERT do?

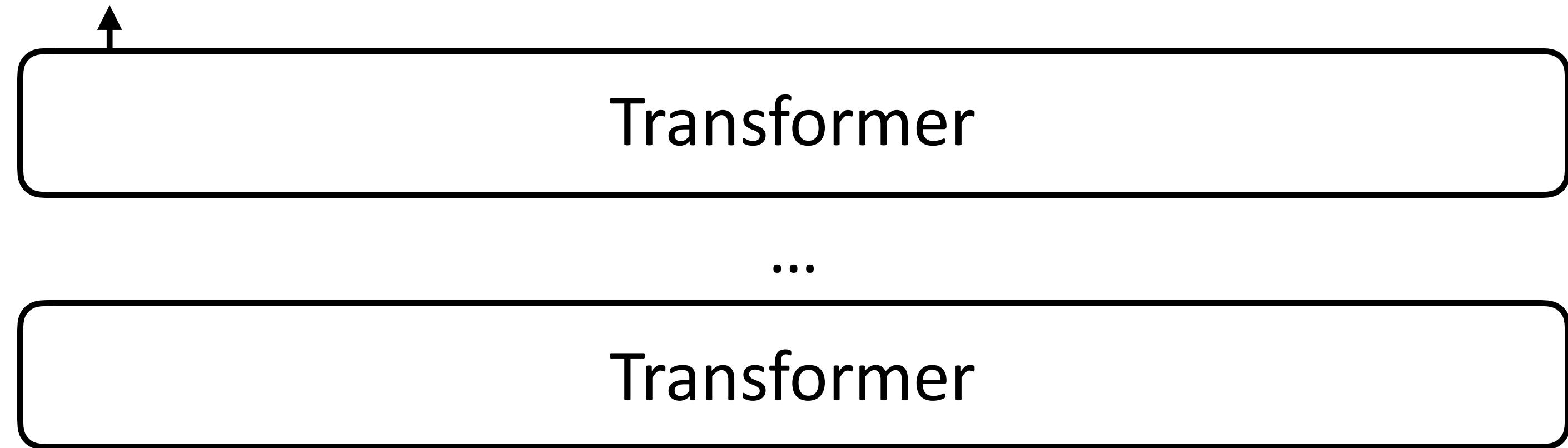


- ▶ CLS token is used to provide classification decisions
- ▶ Sentence pair tasks (entailment): feed both sentences into BERT
- ▶ BERT can also do tagging by predicting tags at each word piece

Devlin et al. (2019)

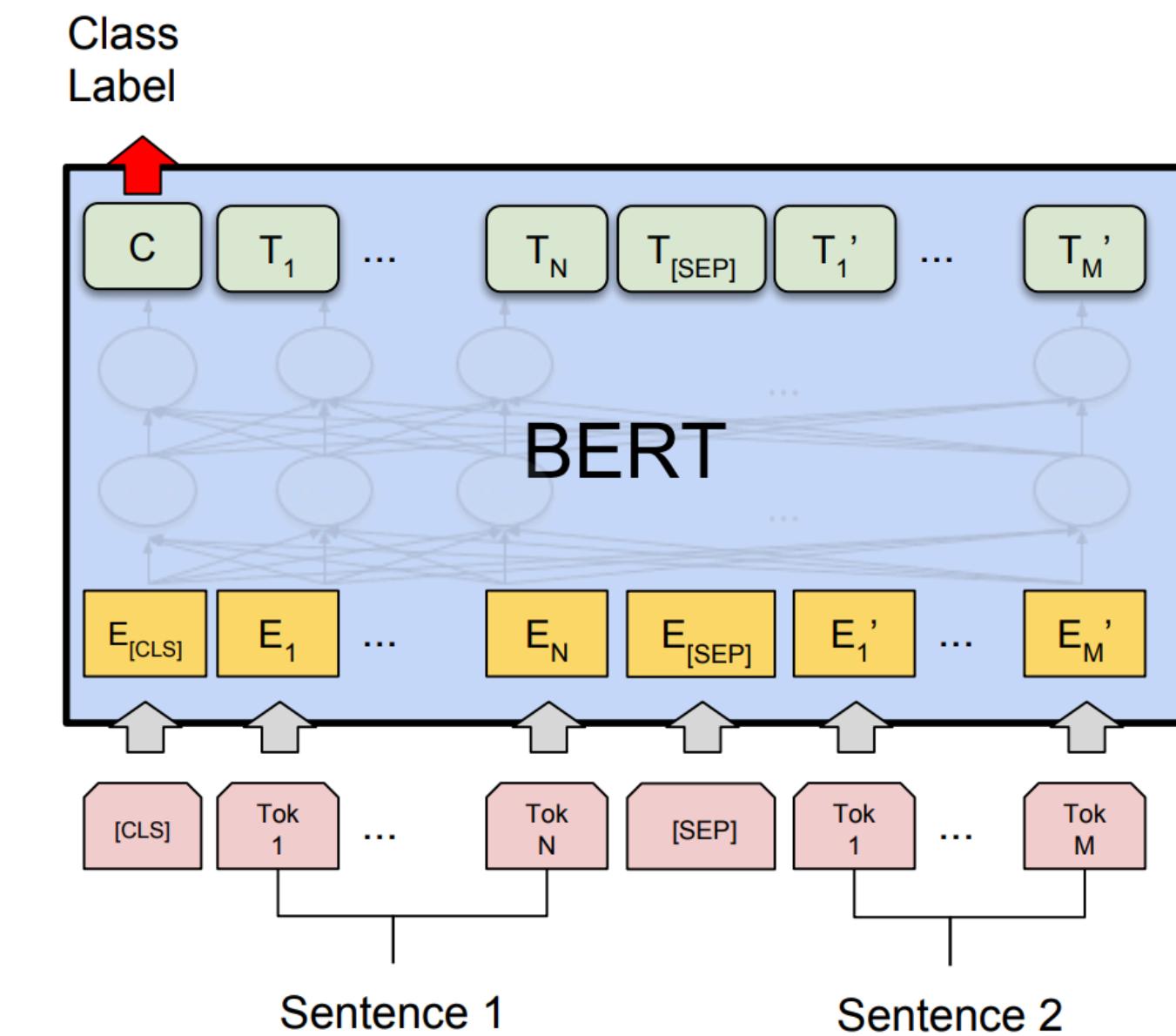
What can BERT do?

Entails



[CLS] A boy plays in the snow [SEP] A boy is outside

- ▶ How does BERT model this sentence pair stuff?
- ▶ Transformers can capture interactions between the two sentences, even though the NSP objective doesn't really cause this to happen



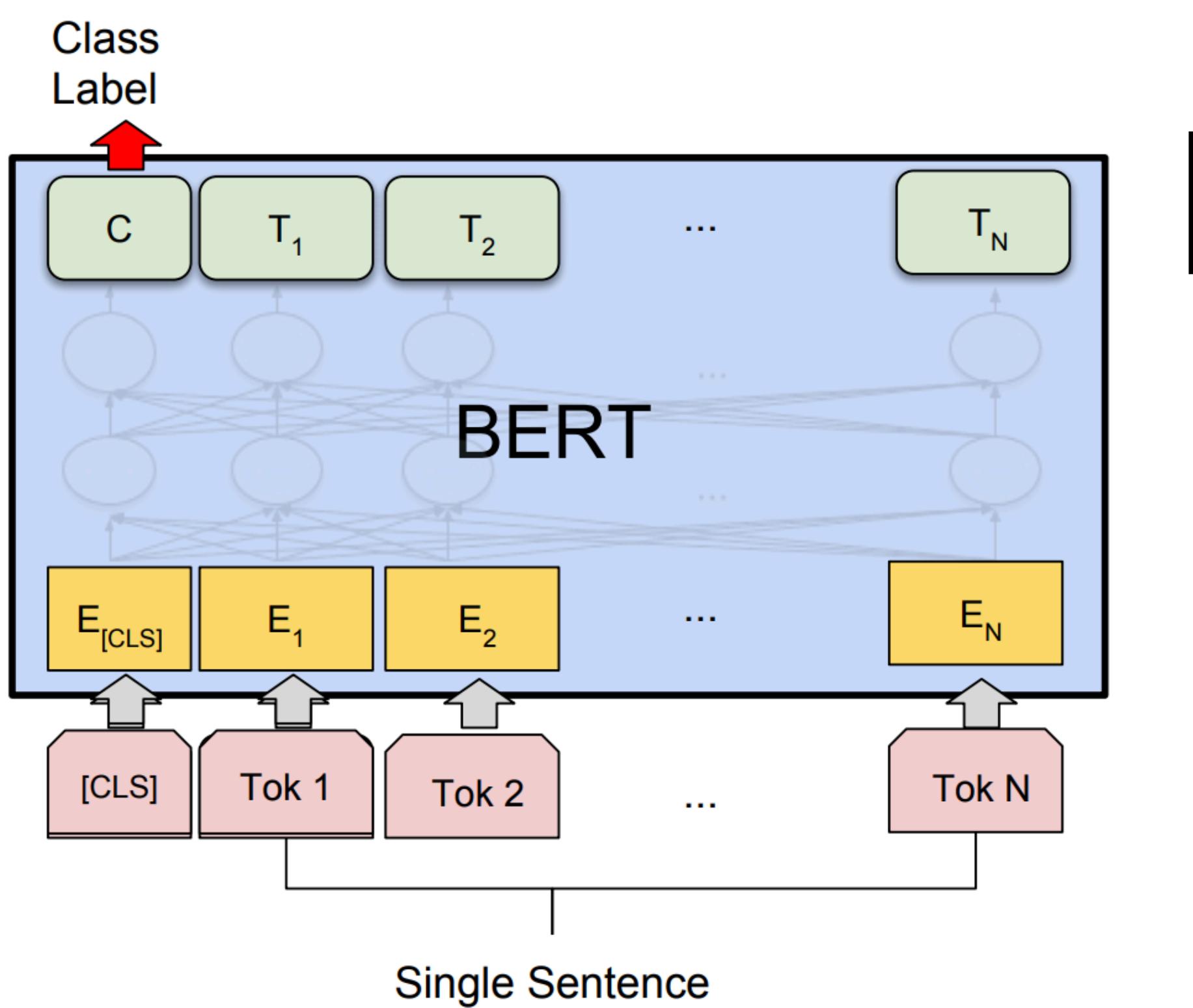
(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG

What can BERT NOT do?

- ▶ BERT **cannot** generate text (at least not in an obvious way)
- ▶ Not an autoregressive model, can do weird things like stick a [MASK] at the end of a string, fill in the mask, and repeat
- ▶ Masked language models are intended to be used primarily for “analysis” tasks

Fine-tuning BERT

- ▶ Fine-tune for 1-3 epochs, batch size 2-32, learning rate 2e-5 - 5e-5



(b) Single Sentence Classification Tasks:
SST-2, CoLA

- ▶ Large changes to weights up here (particularly in last layer to route the right information to [CLS])
- ▶ Smaller changes to weights lower down in the transformer
- ▶ Small LR and short fine-tuning schedule mean weights don't change much
- ▶ More complex “triangular learning rate” schemes exist

Fine-tuning BERT

Pretraining	Adaptation	NER CoNLL 2003	SA SST-2	Nat. lang. inference MNLI	SICK-E	Semantic textual similarity	MRPC	STS-B
Skip-thoughts	❄️	-	81.8	62.9	-	86.6	75.8	71.8
ELMo	❄️	91.7	91.8	79.6	86.3	86.1	76.0	75.9
	🔥	91.9	91.2	76.4	83.3	83.3	74.7	75.5
	Δ=🔥-❄️	0.2	-0.6	-3.2	-3.3	-2.8	-1.3	-0.4
BERT-base	❄️	92.2	93.0	84.6	84.8	86.4	78.1	82.9
	🔥	92.4	93.5	84.6	85.8	88.7	84.8	87.1
	Δ=🔥-❄️	0.2	0.5	0.0	1.0	2.3	6.7	4.2

- ▶ BERT is typically better if the whole network is fine-tuned, unlike ELMo

Evaluation: GLUE

Corpus	Train	Test	Task	Metrics	Domain
Single-Sentence Tasks					
CoLA	8.5k	1k	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
Similarity and Paraphrase Tasks					
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	391k	paraphrase	acc./F1	social QA questions
Inference Tasks					
MNLI	393k	20k	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	146	coreference/NLI	acc.	fiction books

Results

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
BERT _{BASE}	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
BERT _{LARGE}	86.7/85.9	72.1	91.1	94.9	60.5	86.5	89.3	70.1	81.9

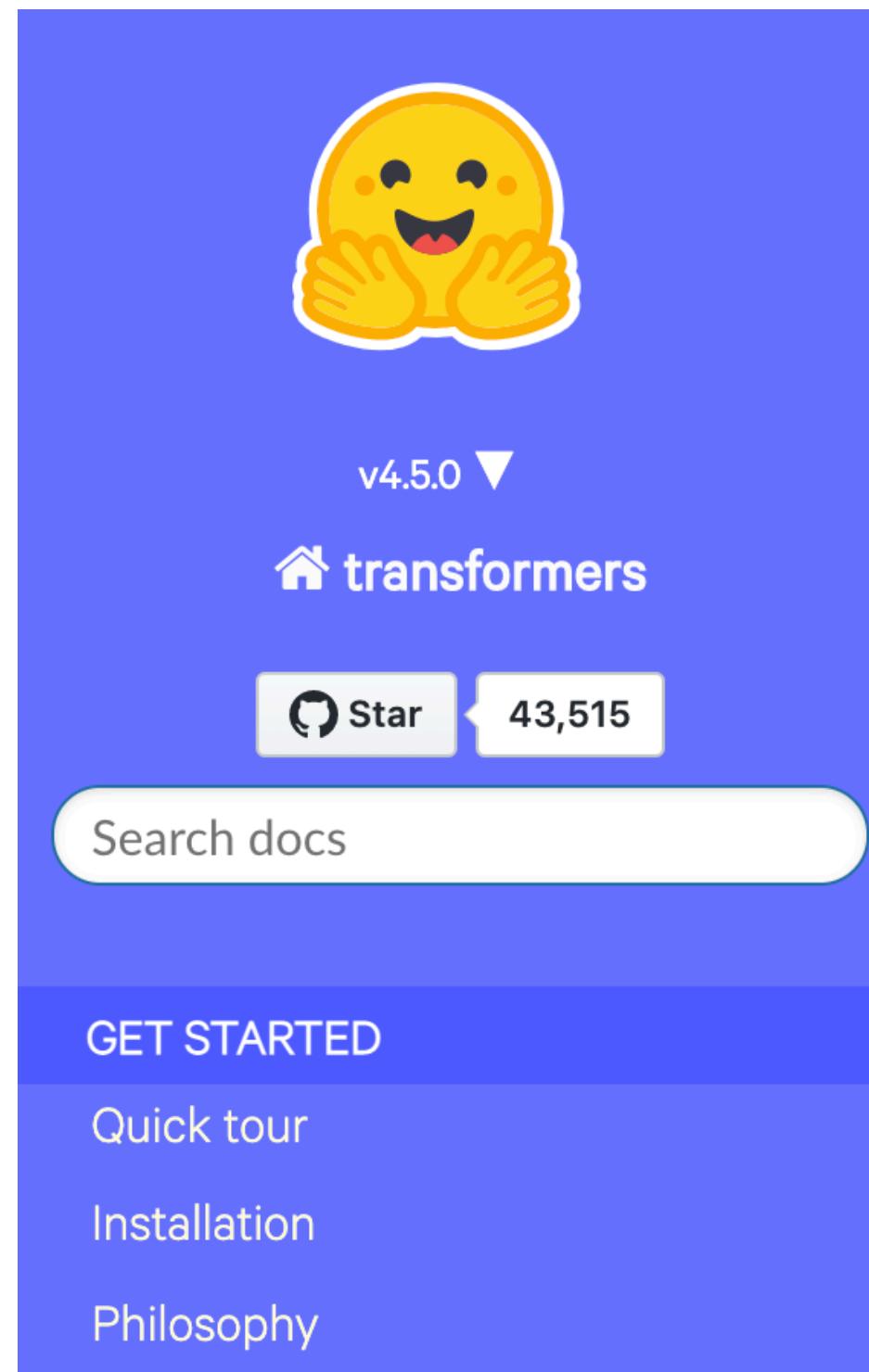
- ▶ Huge improvements over prior work (even compared to ELMo)
- ▶ Effective at “sentence pair” tasks: textual entailment (does sentence A imply sentence B), paraphrase detection

RoBERTa

- ▶ “Robustly optimized BERT”
- ▶ 160GB of data instead of 16 GB
- ▶ Dynamic masking: standard BERT uses the same MASK scheme for every epoch, RoBERTa recomputes them
- ▶ New training + more data = better performance

Model	data	bsz	steps	SQuAD (v1.1/2.0)	MNLI-m	SST-2
RoBERTa						
with BOOKS + WIKI	16GB	8K	100K	93.6/87.3	89.0	95.3
+ additional data (§3.2)	160GB	8K	100K	94.0/87.7	89.3	95.6
+ pretrain longer	160GB	8K	300K	94.4/88.7	90.0	96.1
+ pretrain even longer	160GB	8K	500K	94.6/89.4	90.2	96.4

BERT _{LARGE}	with BOOKS + WIKI	13GB	256	1M	90.9/81.8	86.6	93.7



Docs » Transformers

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MODELS

FORUM

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Transformers

State-of-the-art Natural Language Processing for Pytorch and TensorFlow 2.0.

Transformers (formerly known as *pytorch-transformers* and *pytorch-pretrained-bert*) provides general-purpose architectures (BERT, GPT-2, RoBERTa, XLM, DistilBert, XLNet...) for Natural Language Understanding (NLU) and Natural Language Generation (NLG) with over 32+ pretrained models in 100+ languages and deep interoperability between TensorFlow 2.0 and PyTorch.

This is the documentation of our repository [transformers](#).

GPT/GPT2

OpenAI GPT/GPT2

- ▶ “ELMo with transformers” (works better than ELMo)
- ▶ Train a single unidirectional transformer LM on long contexts
- ▶ GPT2: trained on 40GB of text collected from upvoted links from reddit
- ▶ 1.5B parameters — by far the largest of these models trained as of March 2019
- ▶ Because it's a language model, we can **generate** from it

Parameters	Layers	d_{model}
117M	12	768
345M	24	1024
762M	36	1280
1542M	48	1600

OpenAI GPT2

**SYSTEM PROMPT
(HUMAN-WRITTEN)**

Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today.

**MODEL COMPLETION
(MACHINE-WRITTEN,
SECOND TRY)**

The 19-year-old singer was caught on camera being escorted out of the store by security guards.

The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back.

Scroll down for video

Shoplifting: Miley Cyrus was caught shoplifting from Abercrombie and Fitch on Hollywood Boulevard today (pictured)

The singer was wearing a black hoodie with the label 'Blurred Lines' on the front and 'Fashion Police' on the back

The singer was also wearing a pair of black-rimmed glasses, a black jacket, black jeans and black sandals.

She was carrying a pair of black and white striped gloves and a small black bag.

slide credit:
OpenAI

Open Questions

- 1) How novel is the stuff being generated? (Is it just doing nearest neighbors on a large corpus?)
- 2) How do we understand and distill what is learned in this model?
- 3) How do we harness these priors for conditional generation tasks (summarization, generate a report of a basketball game, etc.)
- 4) Is this technology dangerous? (OpenAI has only released 774M param model, not 1.5B yet)

Grover

- ▶ Sample from a large language model conditioned on a domain, date, authors, and headline
- ▶ Humans rank Grover-generated propaganda as more realistic than real “fake news”
- ▶ Fine-tuned Grover can detect Grover propaganda easily — authors argue for releasing it for this reason
- ▶ NOTE: Not a GAN, discriminator trained separately from the generator

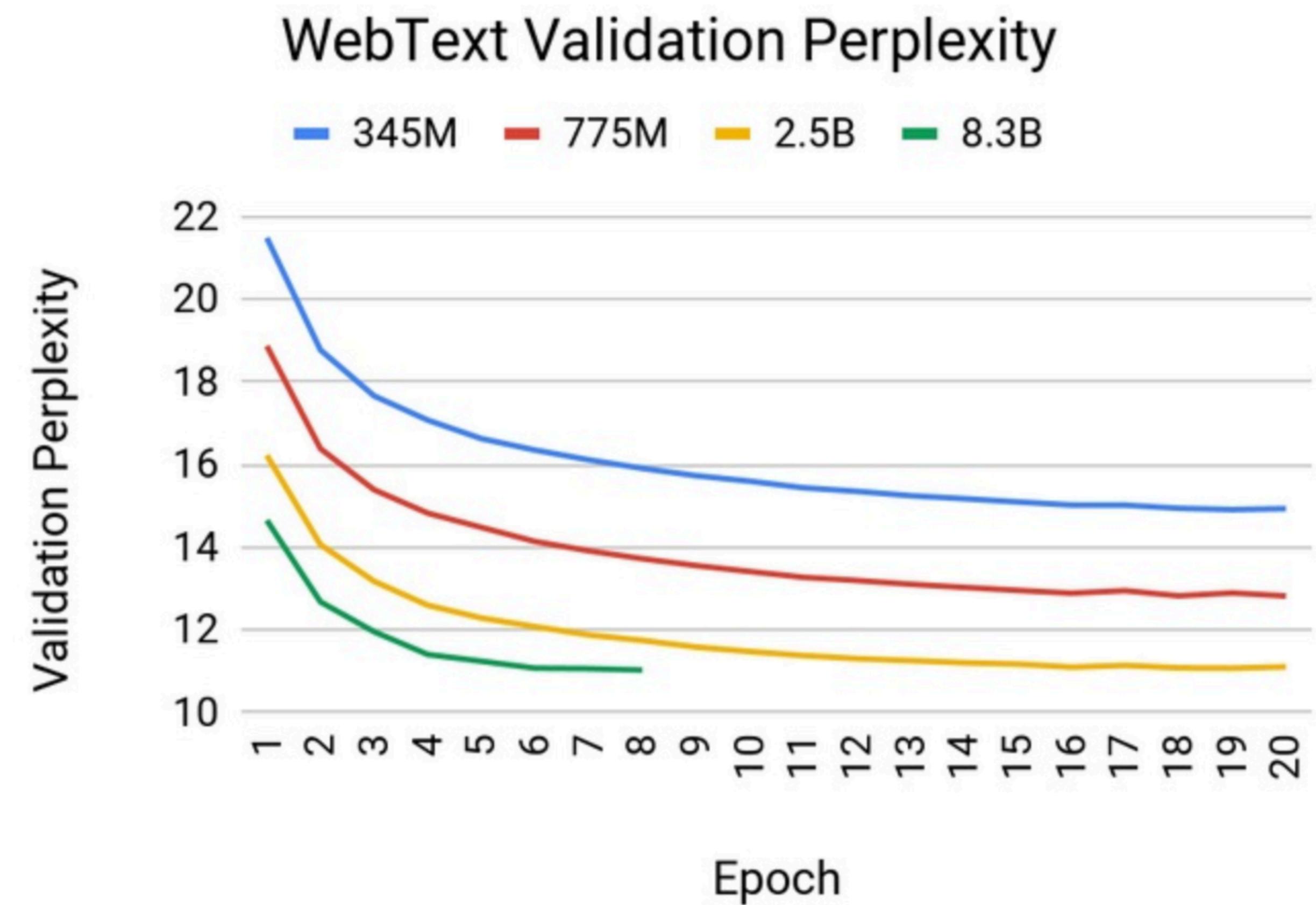
Discriminator size	Unpaired Accuracy			Paired Accuracy		
	Generator size	Generator size	Generator size	Generator size	Generator size	Generator size
Chance	50.0	50.0	50.0	50.0	50.0	50.0
1.5B	GROVER-Mega	92.0	98.5	99.8	97.4	100.0
	GROVER-Large	80.8	91.2	98.4	89.0	96.9
	BERT-Large	73.1	75.9	97.5	84.1	91.5
355M	GPT2	70.1	78.0	90.3	78.8	87.0
	GROVER-Base	70.1	80.0	89.2	77.5	88.2
	BERT-Base	67.2	76.6	84.1	80.0	89.5
124M	GPT2	66.2	71.9	83.5	72.5	79.6
	FastText	63.8	65.6	69.7	65.9	69.0
11M						74.4

Pre-Training Cost (with Google/AWS)

- ▶ BERT: Base \$500, Large \$7000
- ▶ Grover-MEGA: \$25,000
- ▶ XLNet (BERT variant): \$30,000 – \$60,000 (unclear)
- ▶ This is for a single pre-training run...developing new pre-training techniques may require many runs
- ▶ *Fine-tuning* these models can typically be done with a single GPU (but may take 1-3 days for medium-sized datasets)

Pushing the Limits

- ▶ NVIDIA: trained 8.3B parameter GPT model (5.6x the size of GPT-2)
- ▶ Arguably these models are still underfit: larger models still get better held-out perplexities



NVIDIA blog (Narasimhan, August 2019)

Google T5

Number of tokens	Repeats	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
★ Full dataset	0	83.28	19.24	80.88	71.36	26.98	39.82	27.65
2^{29}	64	82.87	19.19	80.97	72.03	26.83	39.74	27.63
2^{27}	256	82.62	19.20	79.78	69.97	27.02	39.71	27.33
2^{25}	1,024	79.55	18.57	76.27	64.76	26.38	39.56	26.80
2^{23}	4,096	76.34	18.33	70.92	59.29	26.37	38.84	25.81

- ▶ Colossal Cleaned Common Crawl: 750 GB of text
- ▶ We still haven't hit the limit of bigger data being useful

BART

- ▶ Sequence-to-sequence BERT variant: permute/make/delete tokens, then predict full sequence autoregressively
- ▶ For downstream tasks: feed document into both encoder + decoder, use decoder hidden state as output
- ▶ Good results on dialogue, summarization tasks

