Lecture 11: Seq2Seq + Attention

Alan Ritter

(many slides from Greg Durrett)

Administrivia

Course Project

Next homework assignment

Final Project

- Groups of 3-4
- Sign up here:
  - https://forms.gle/3u5vC78uBP6eK8Xn7
- **Highly Recommended:** stop by the office hours to chat and get feedback on your project.
- **Scope:** on the order of one of the programming assignments
  - But, need to define the problem, come up with right feature representation, write up results in a formal report.

Selecting a Topic

- Part of your thesis? Great!
- Find a problem you are interested in where you think NLP can help.
- Experiment with one of the algorithms we discussed about in class.
- **First question:** what is the dataset?

Datasets

- Various Semeval Tasks:
  - http://alt.qcri.org/semeval2018/index.php?id=tasks
- Fake News Challenge:
  - http://www.fakenewschallenge.org/
- Machine Translation:
  - http://www.statmt.org/wmt19/robustness.html
- Dialogue:
  - https://github.com/mgalley/DSTC7-End-to-End-Conversation-Modeling
- Many more…

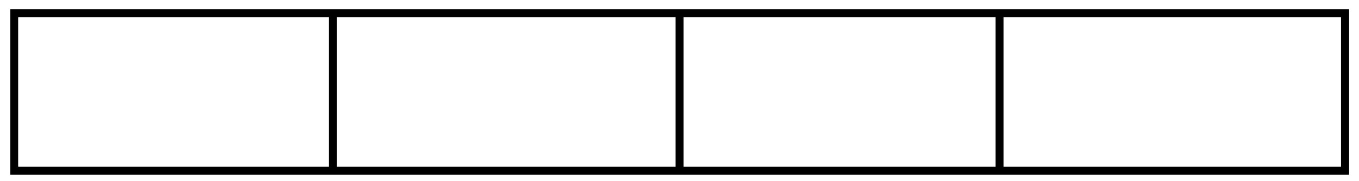
Requirements

- 4 Page Report
- Include empirical analysis of your approach
  - Report performance on dev / test set
  - Compare against some reasonable baseline method.
- In class presentation during scheduled Final Exam time

Advice

- **First question:** is the data available?
- Try to get a simple baseline working as early as possible to determine whether your project idea is feasible.
- Start with a manageable-sized dataset
  - Then scale up…

Recall: CNNs vs. LSTMs



n x k

the movie was good

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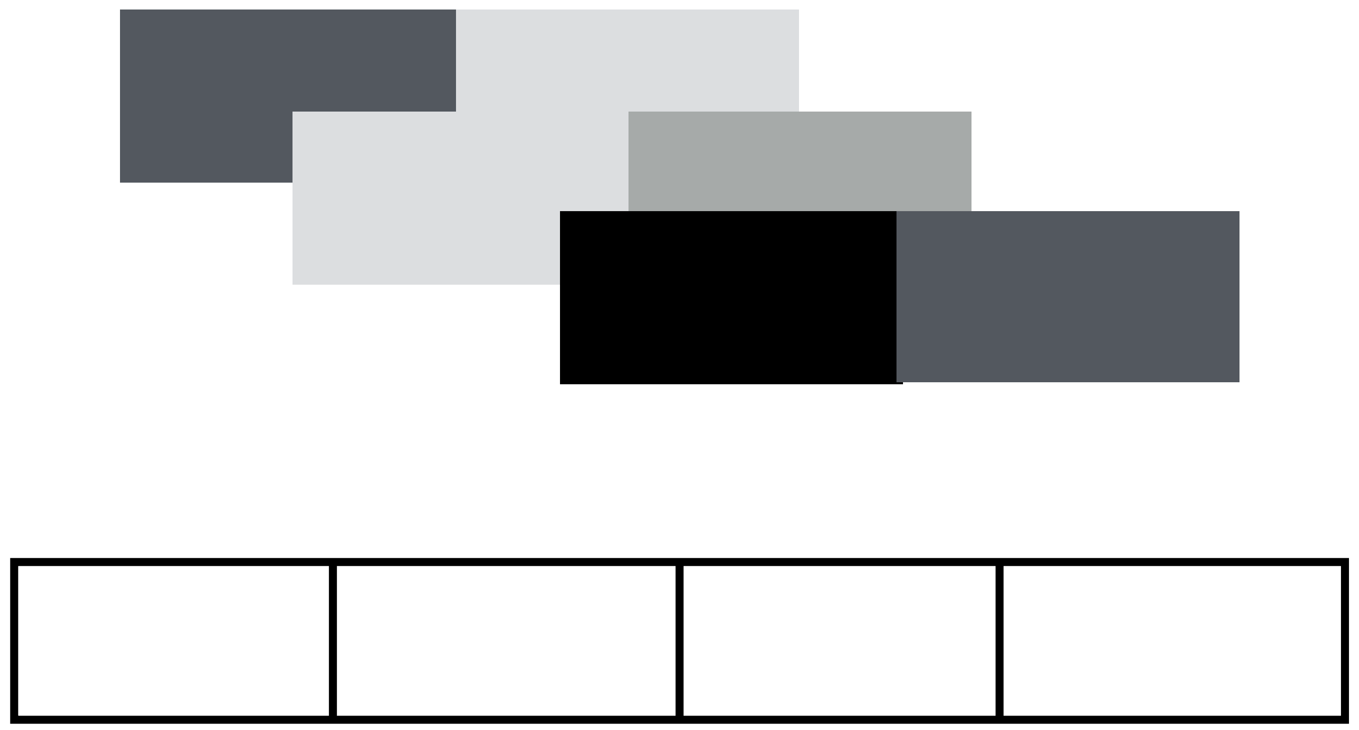

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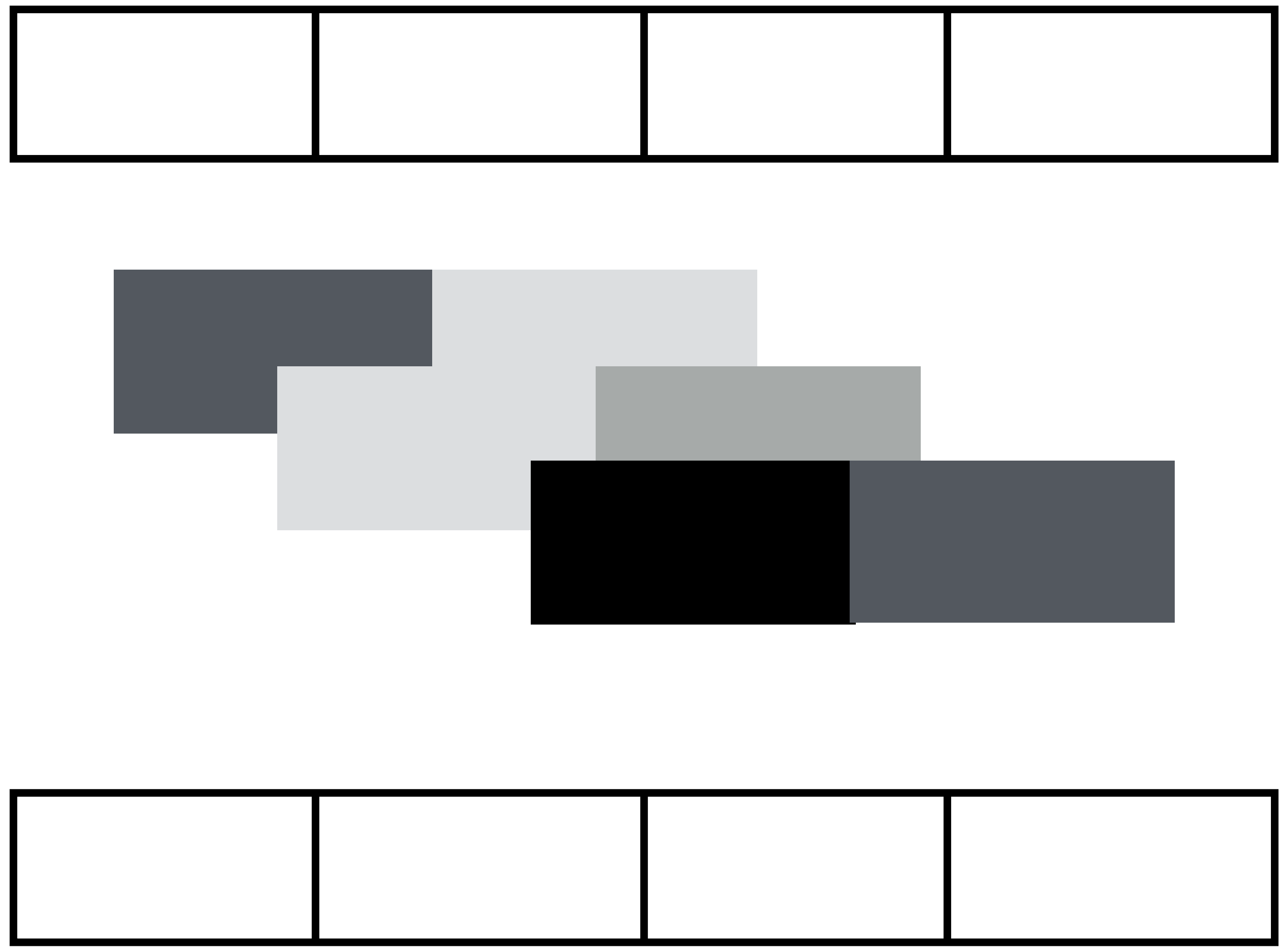

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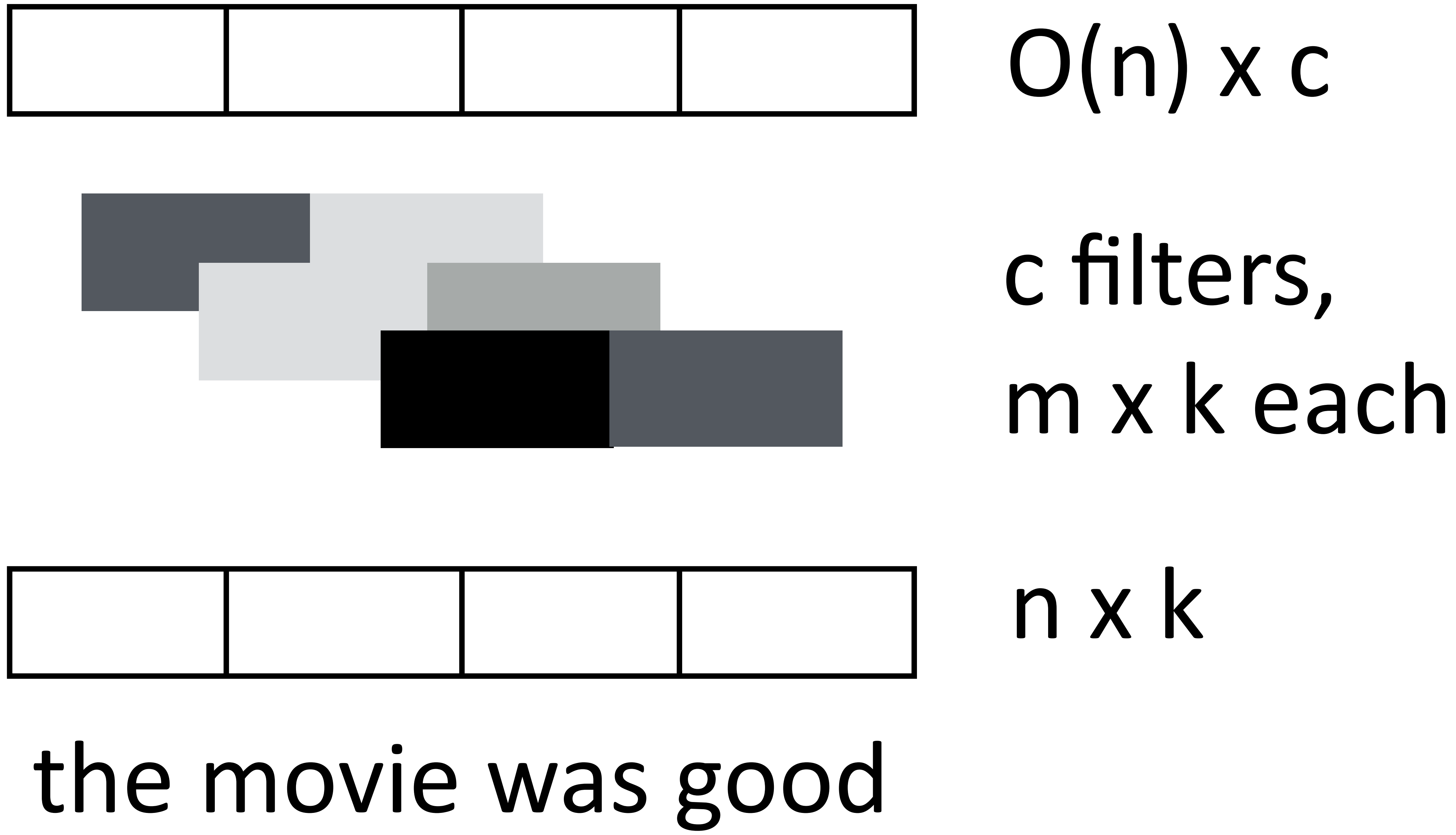

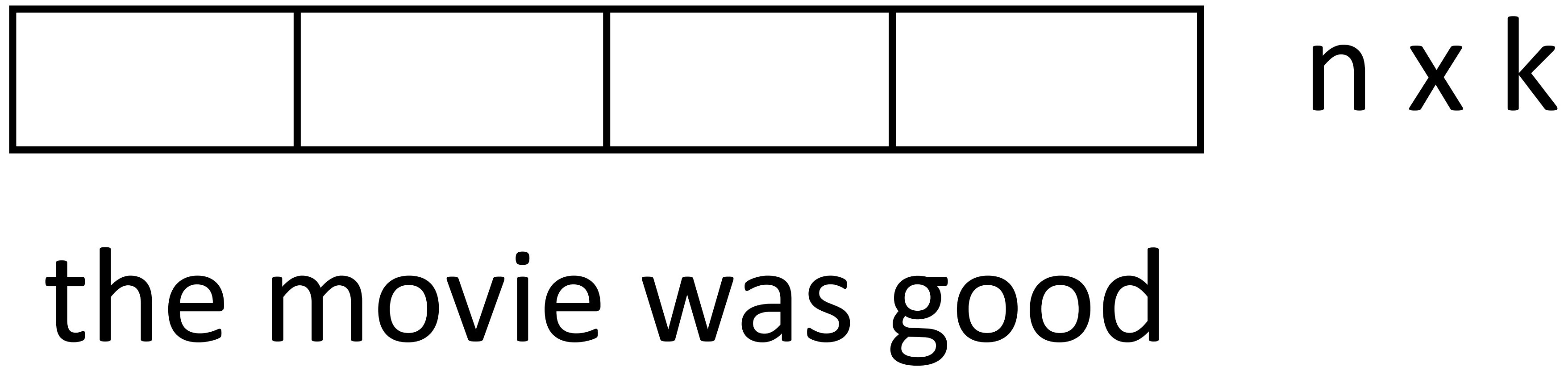

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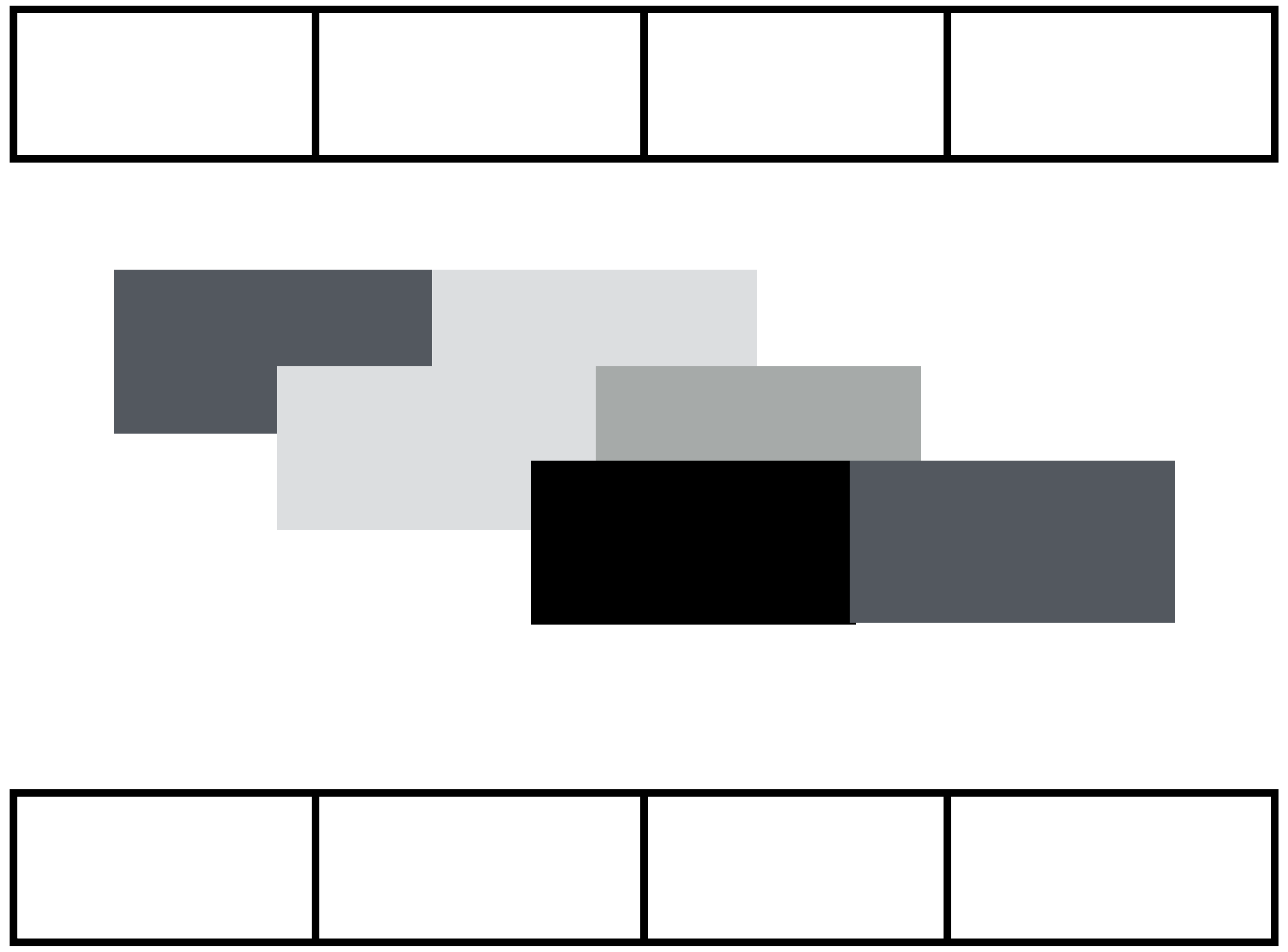

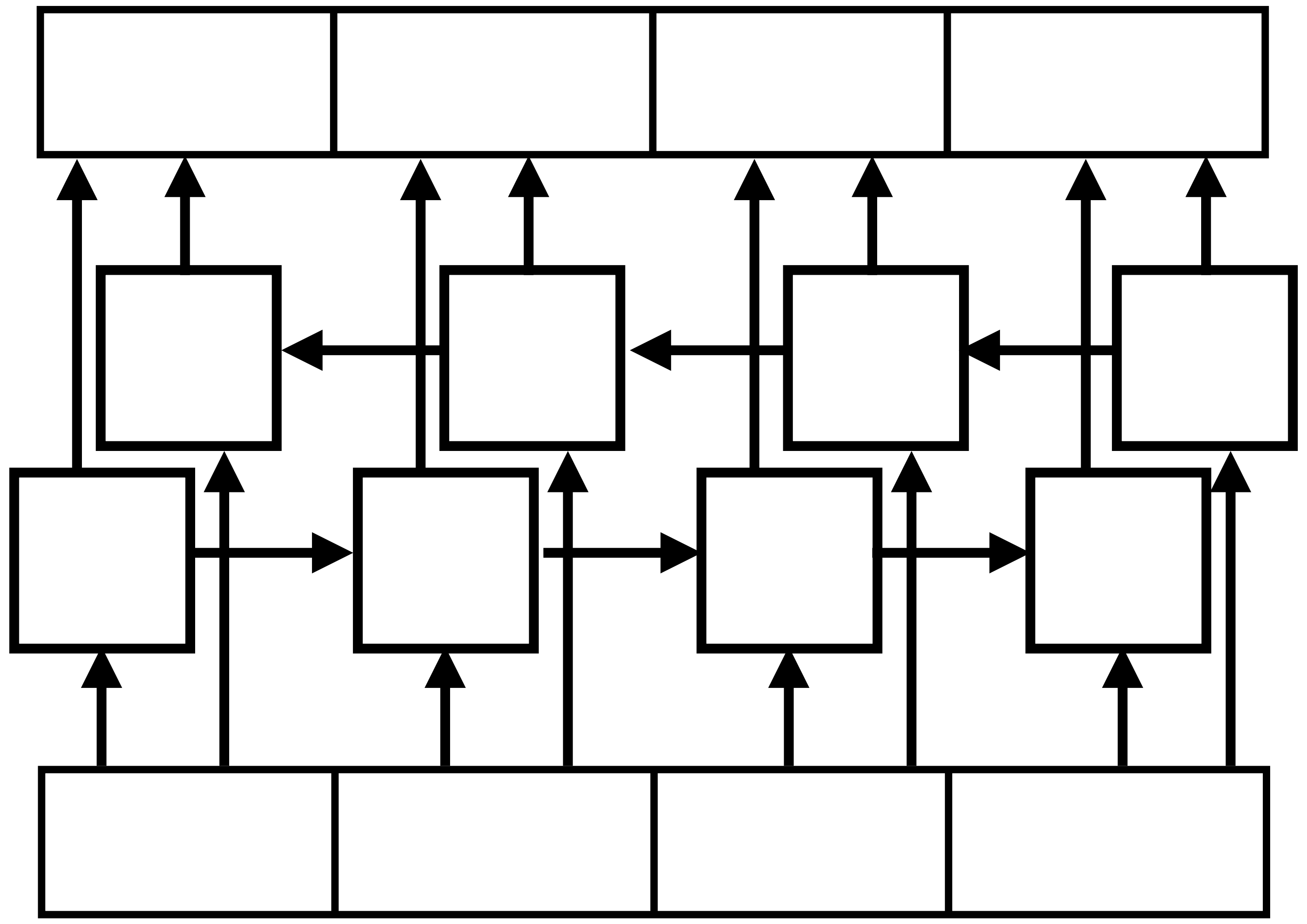

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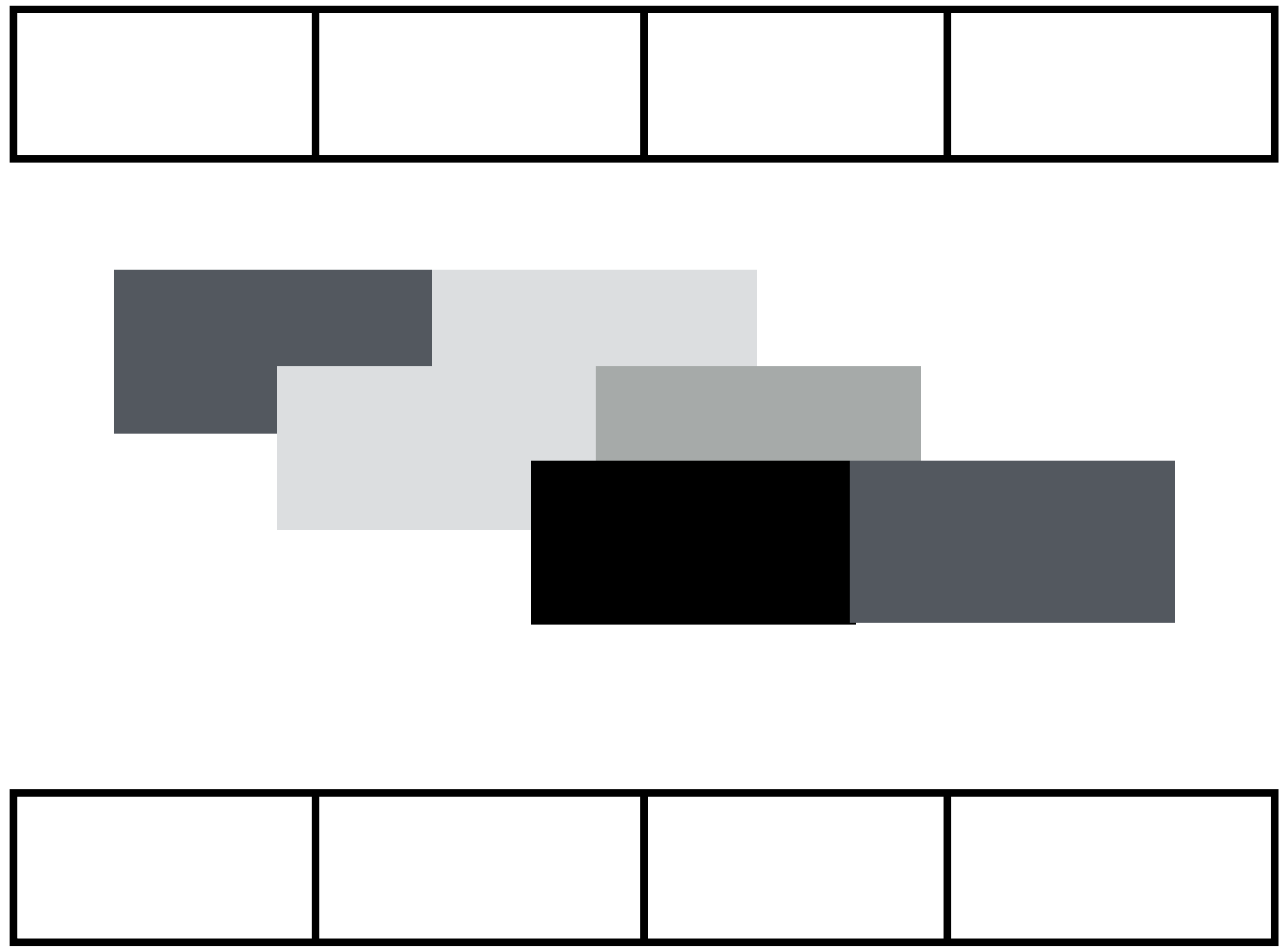
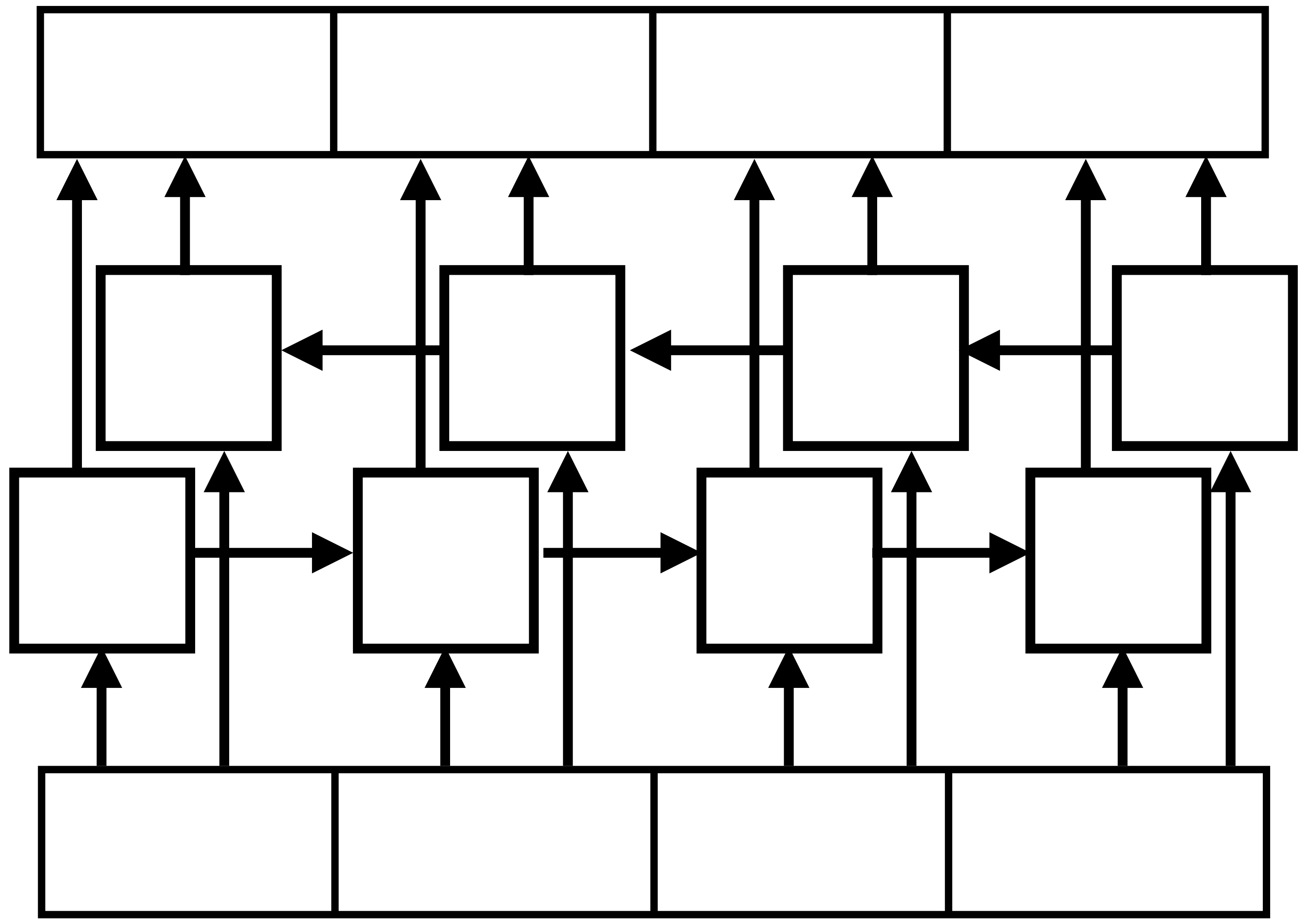
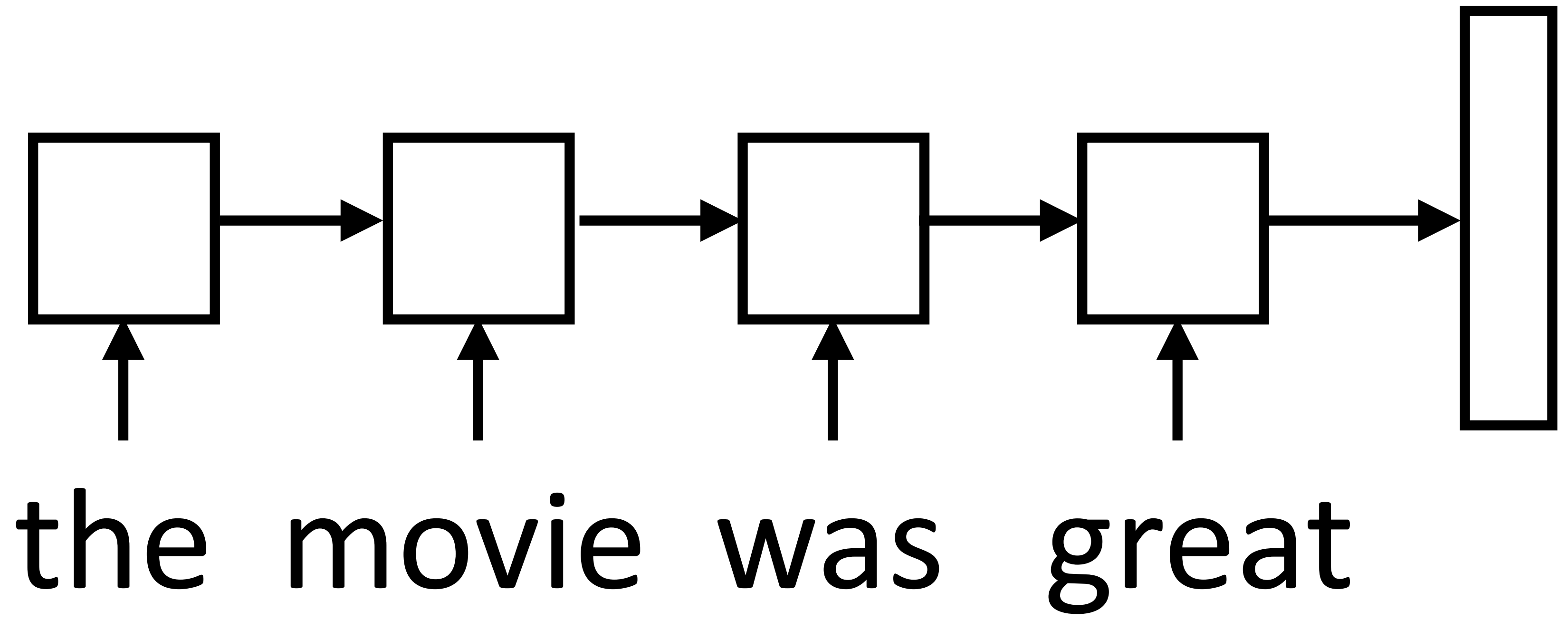




- Both LSTMs and convolutional layers transform the input using context
- LSTM: “globally” looks at the entire sentence (but local for many problems)
- CNN: local depending on filter width + number of layers

Encoder-Decoder

- Encode a sequence into a fixed-sized vector



Sutskever et al. (2014)

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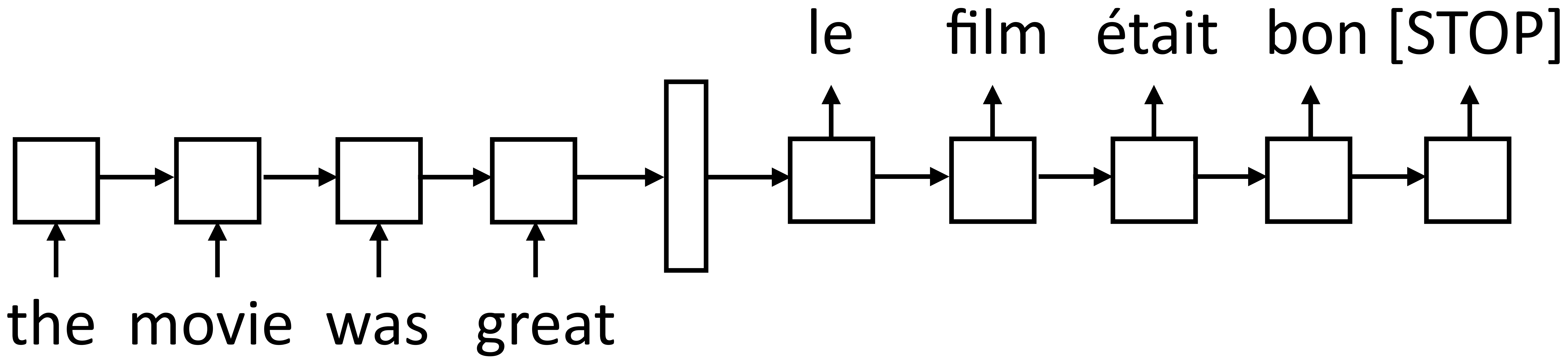

- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

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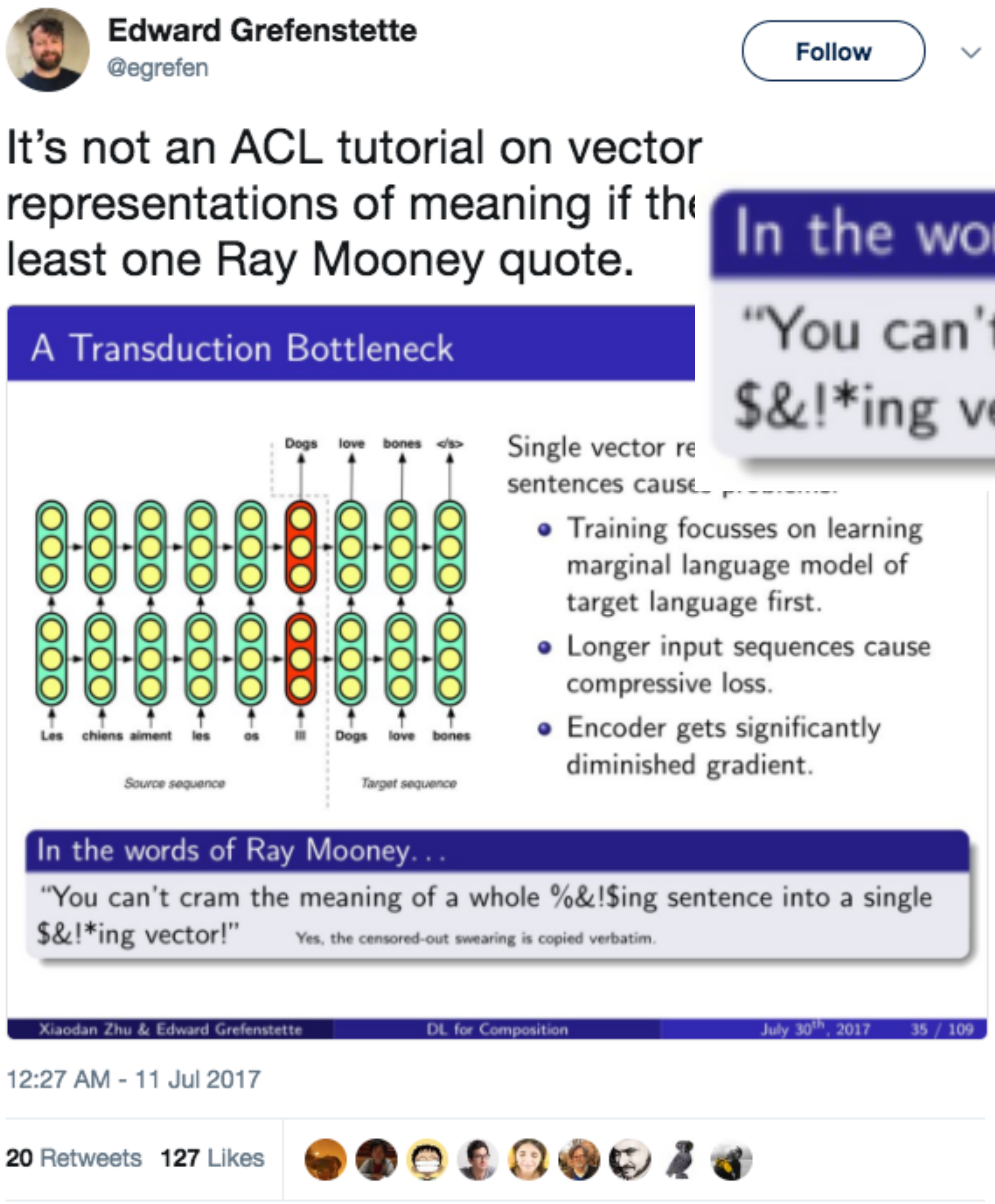
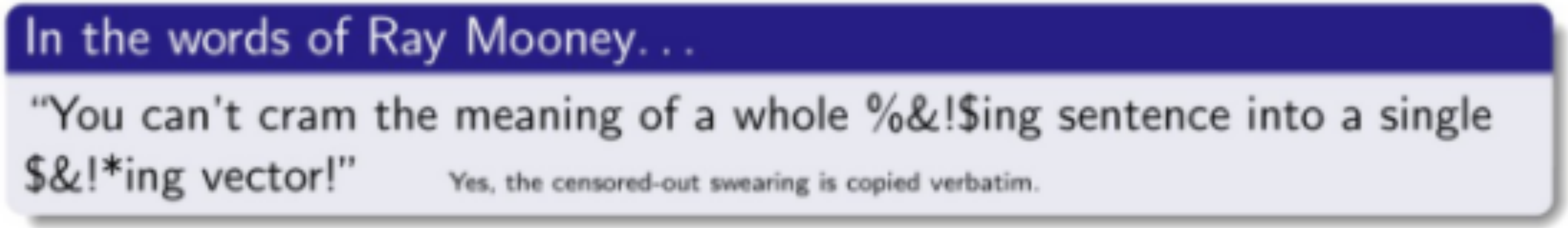
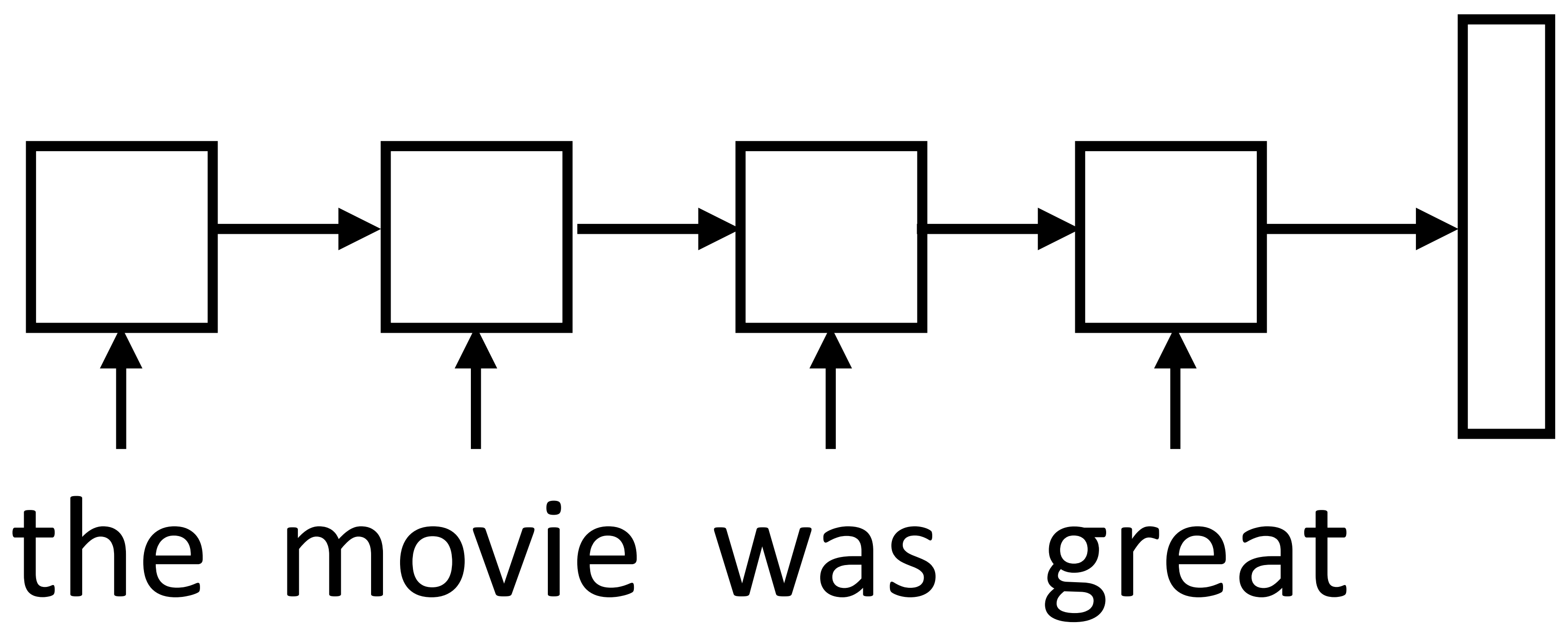




- Is this true? Sort of…we'll come back to this later

Model

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



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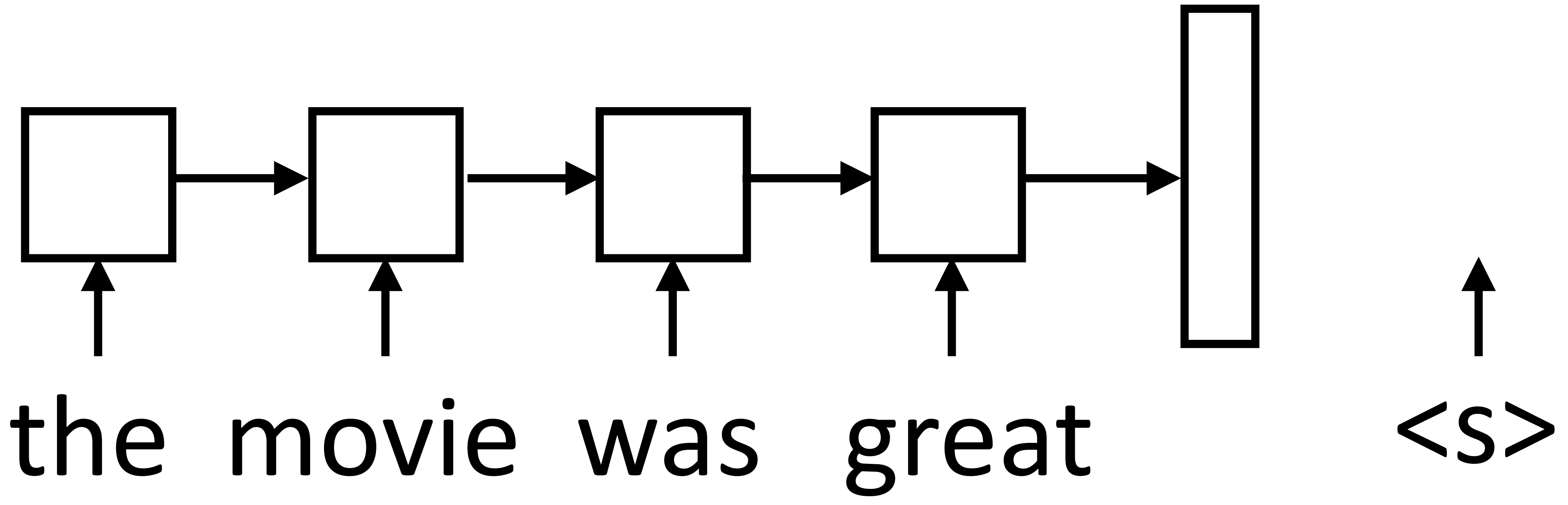

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- W size is |vocab| x |hidden state|, softmax over entire vocabulary

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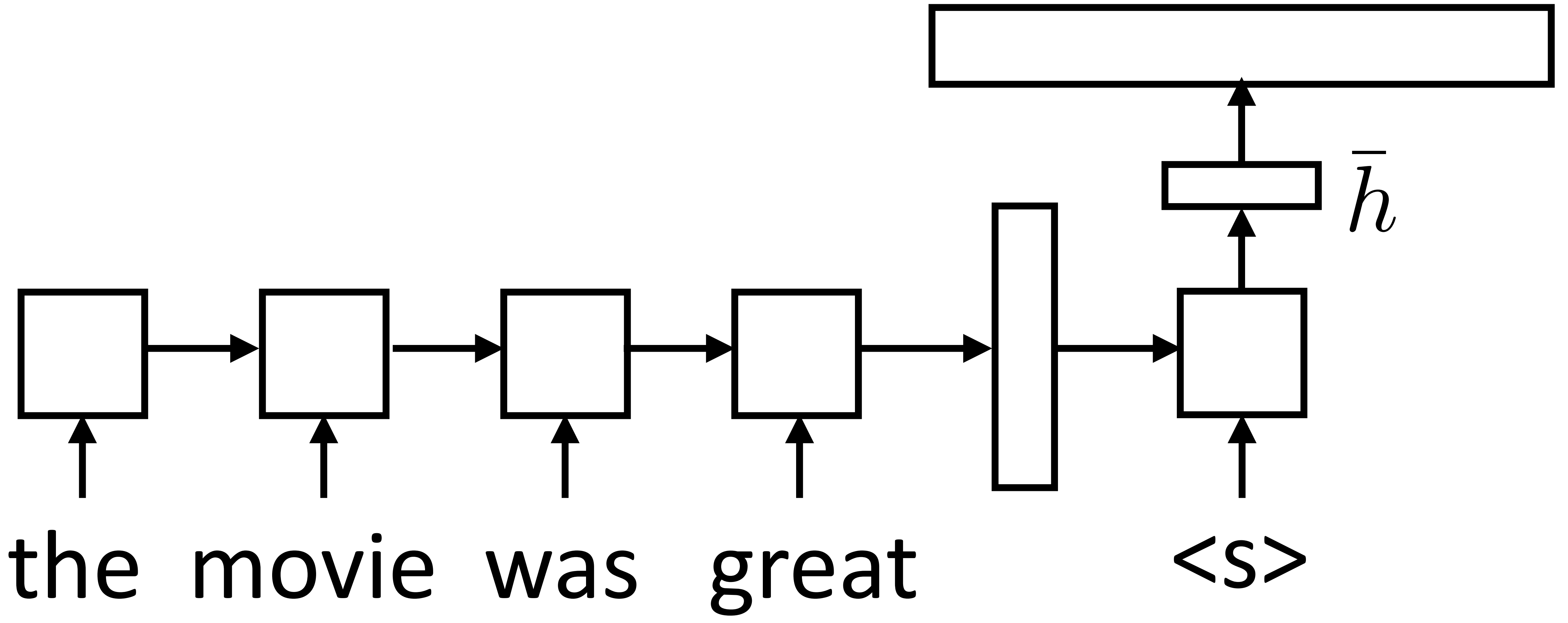

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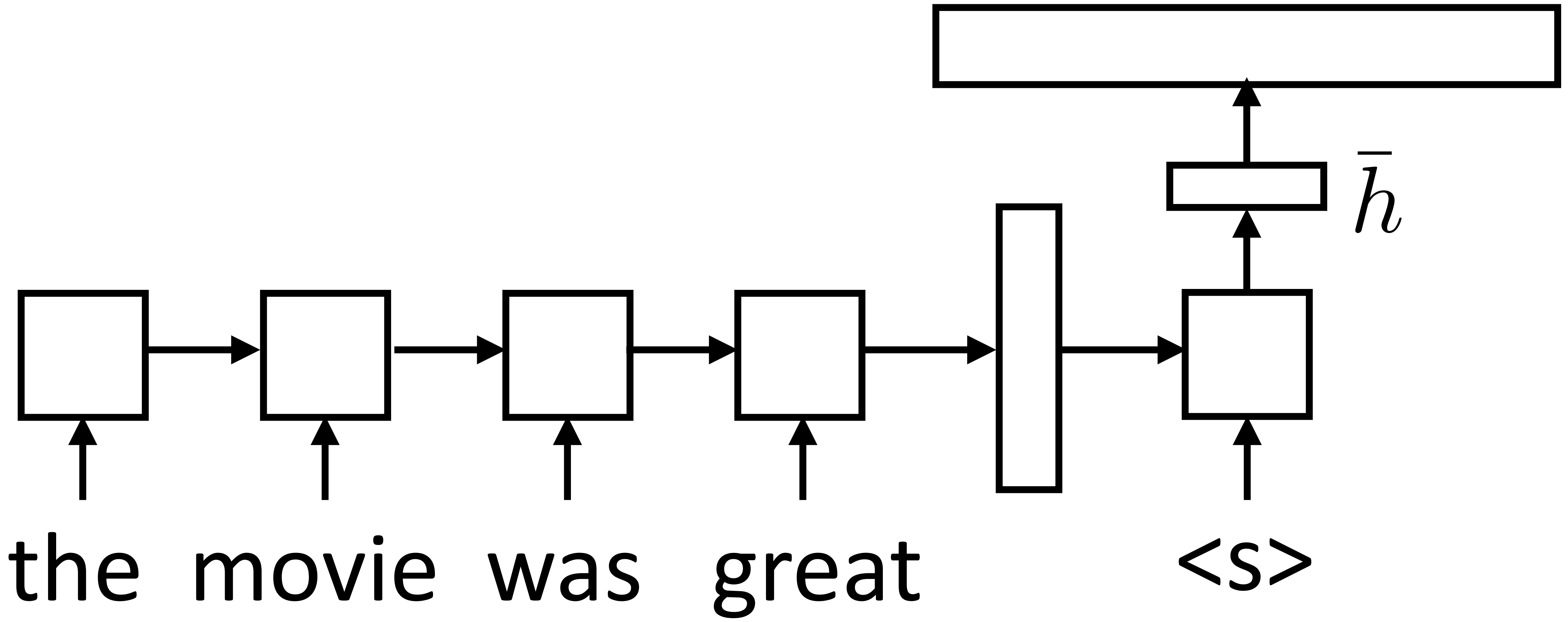

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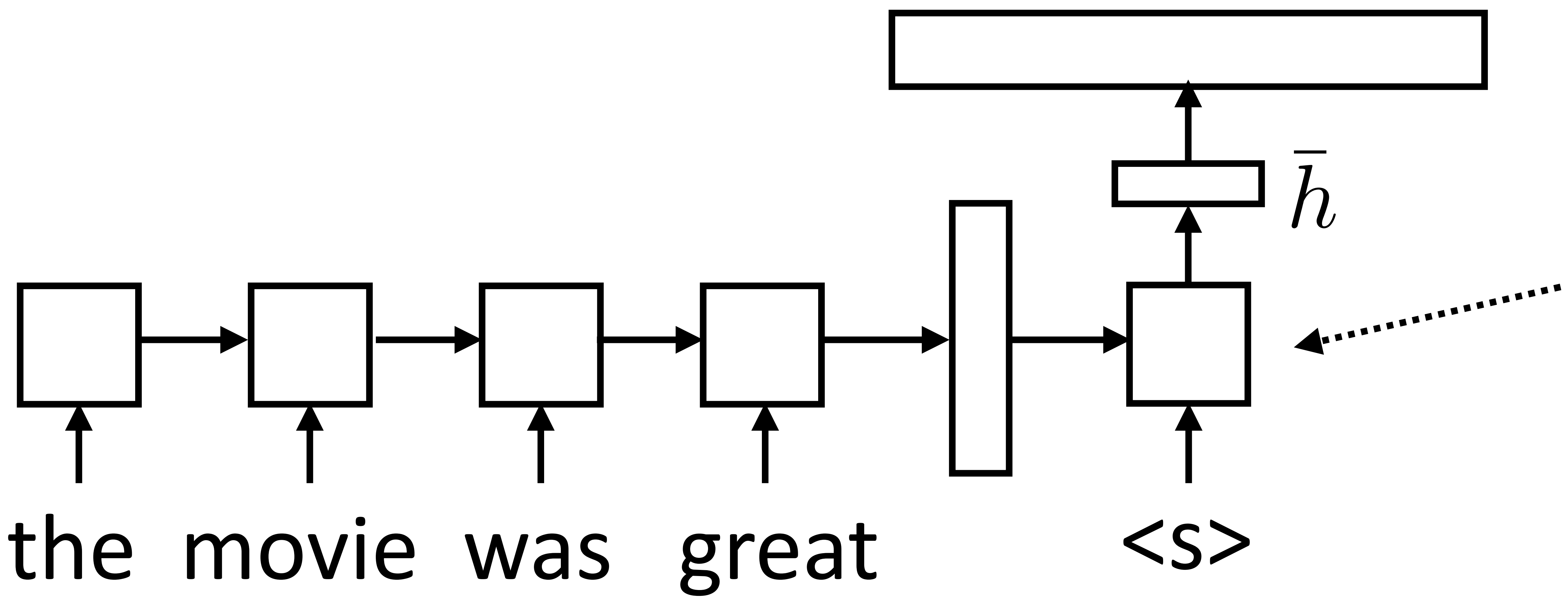

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Decoder has separate parameters from encoder, so this can learn to be a language model (produce a plausible next word given current one)

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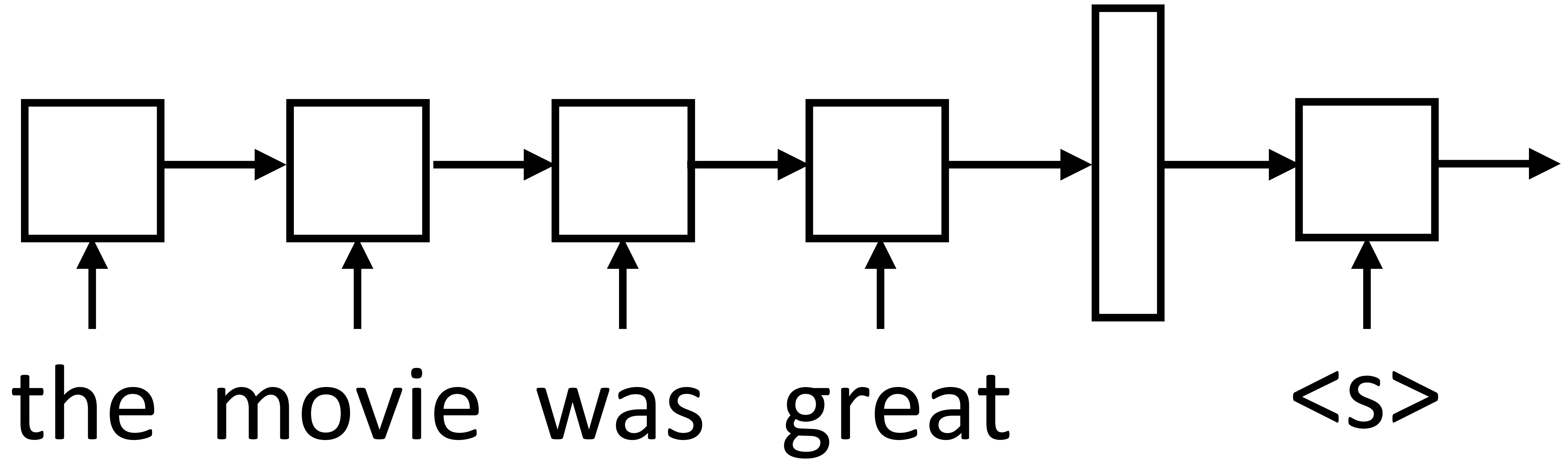

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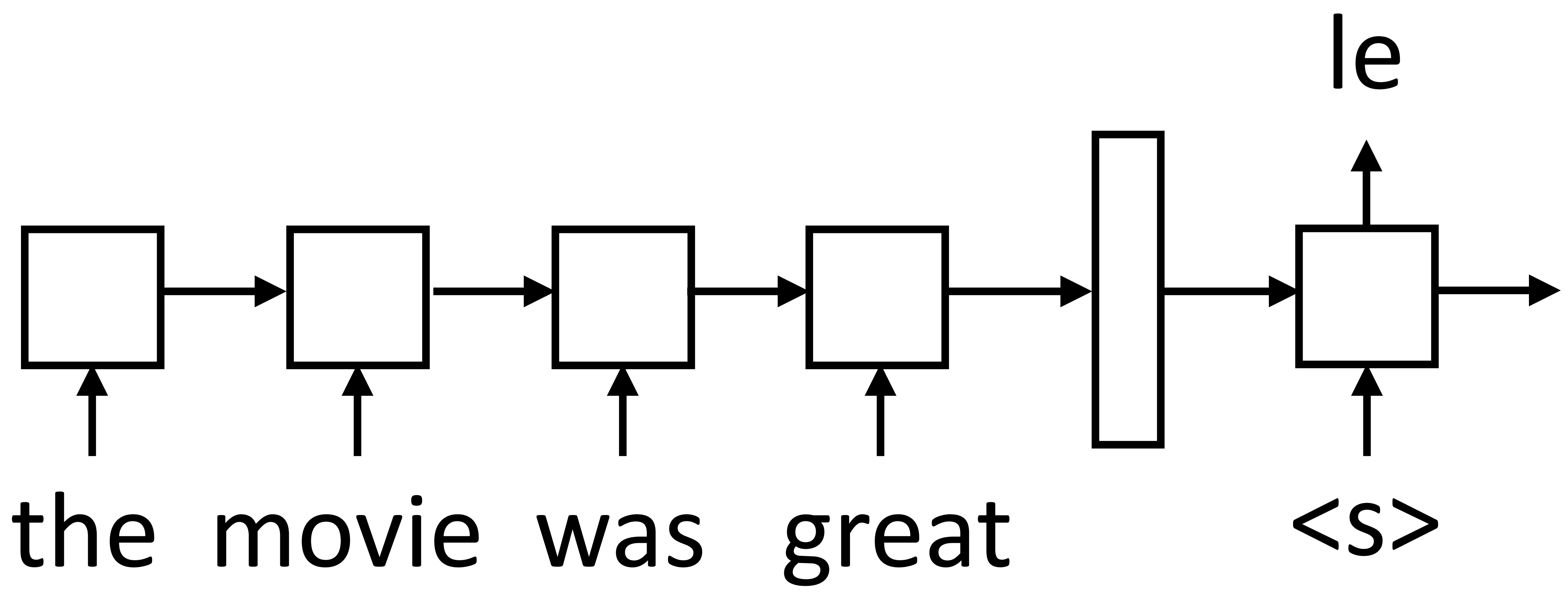

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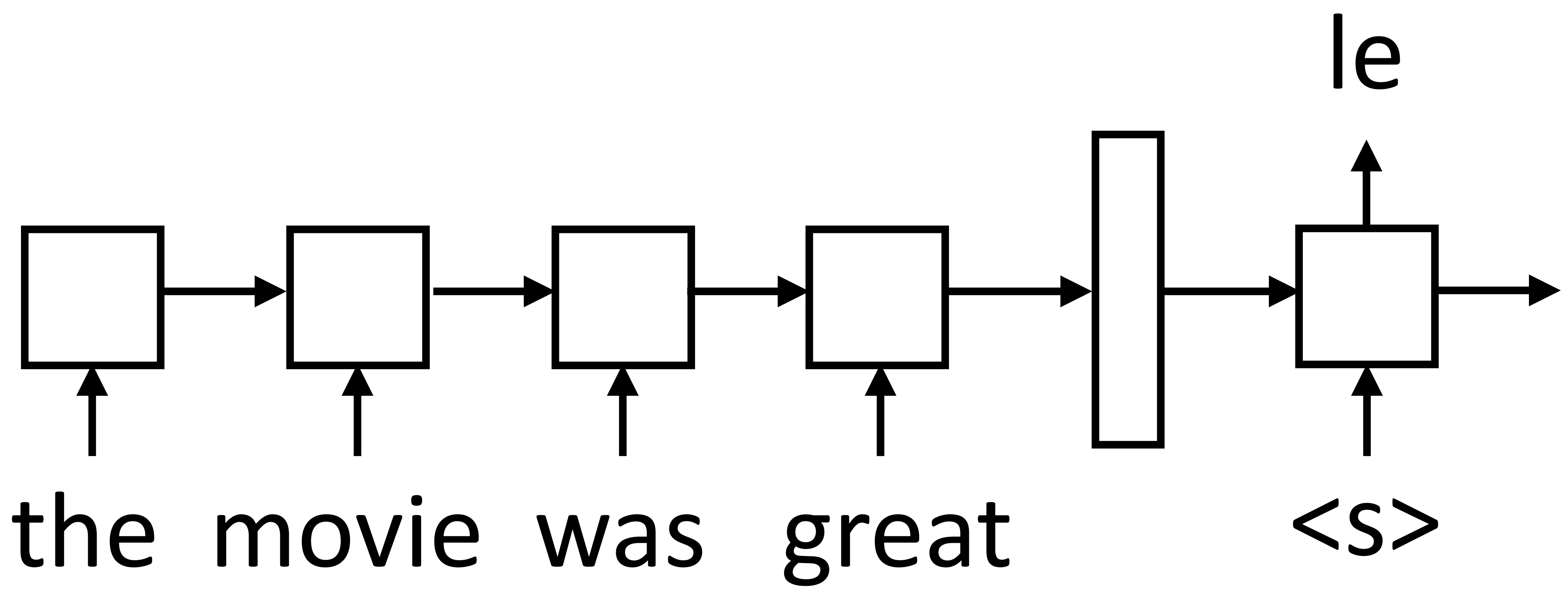

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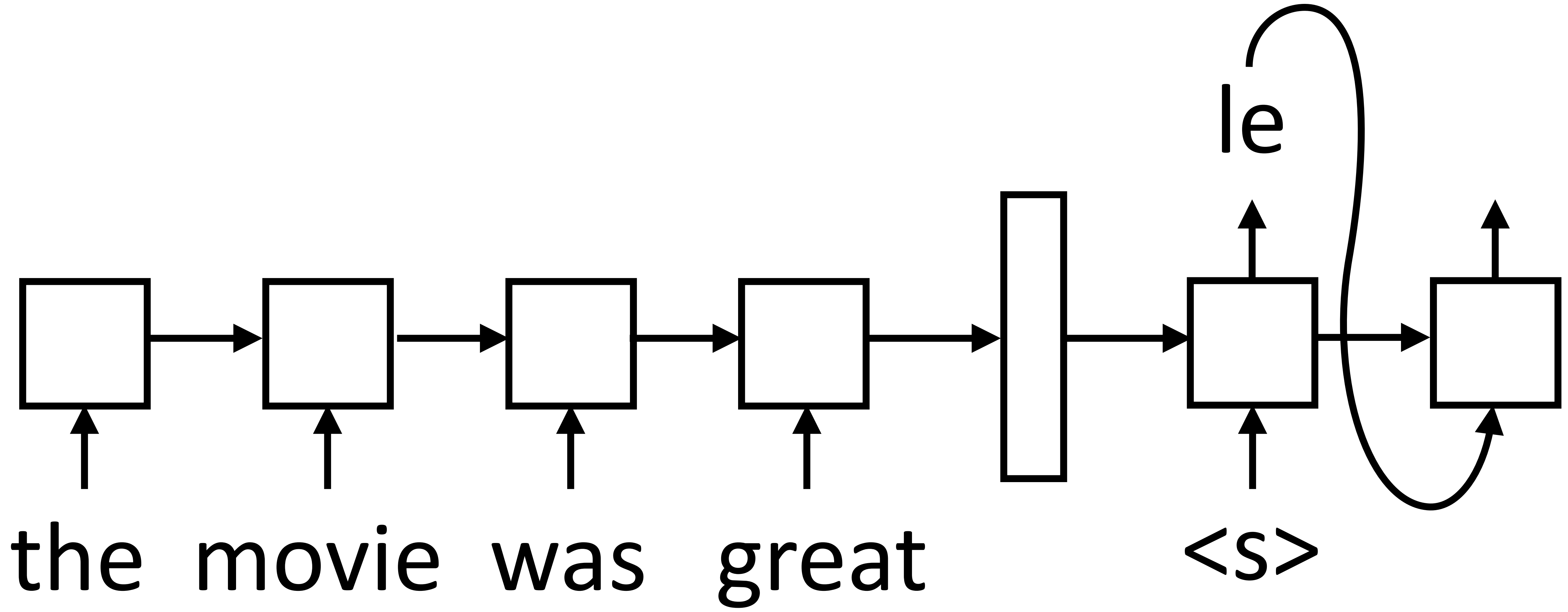

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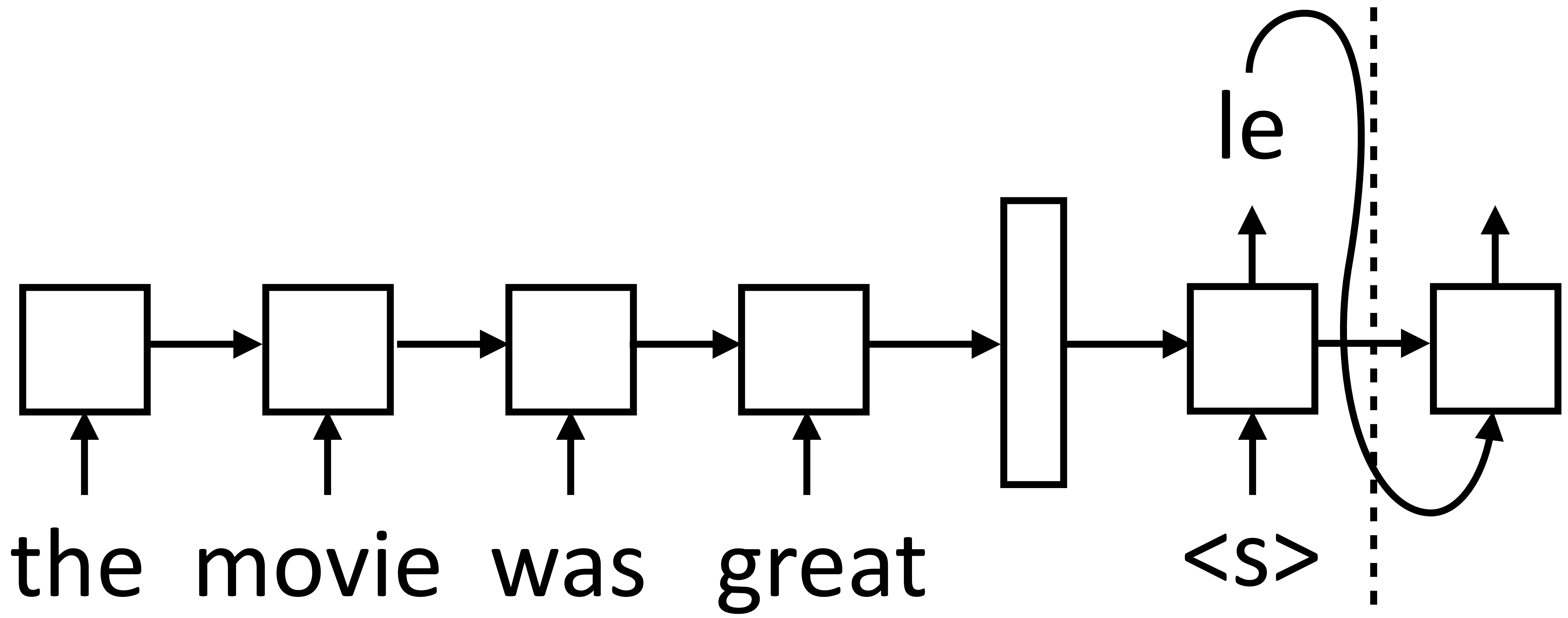

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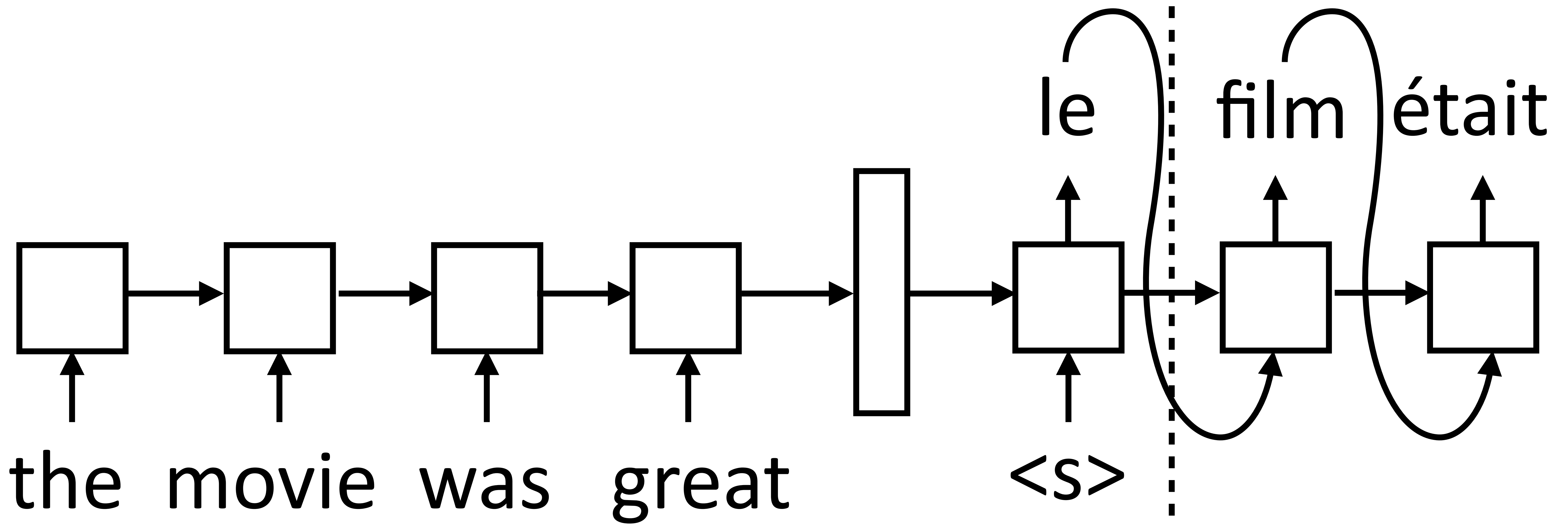

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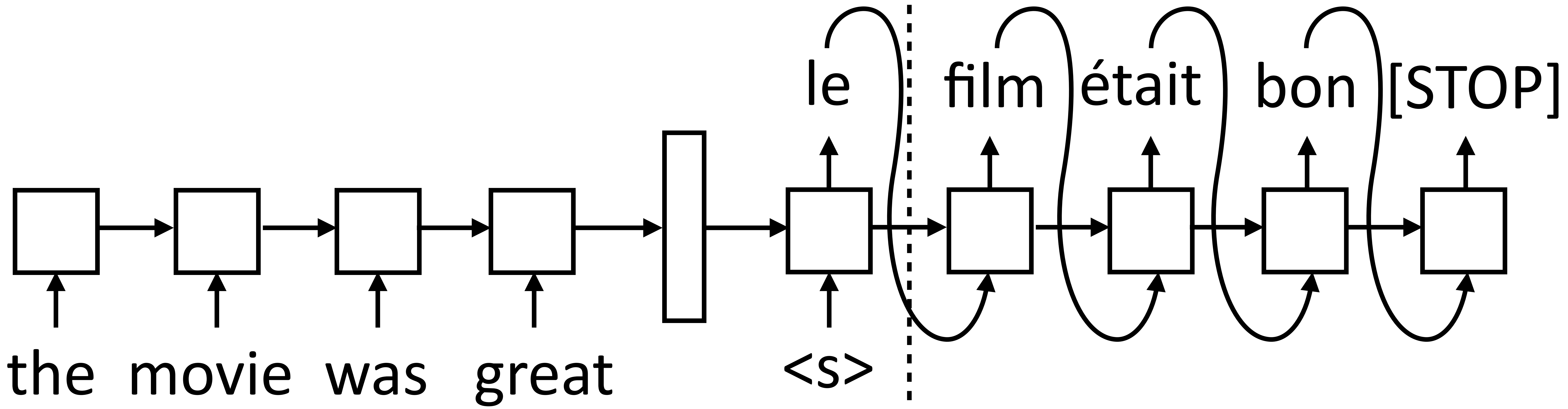

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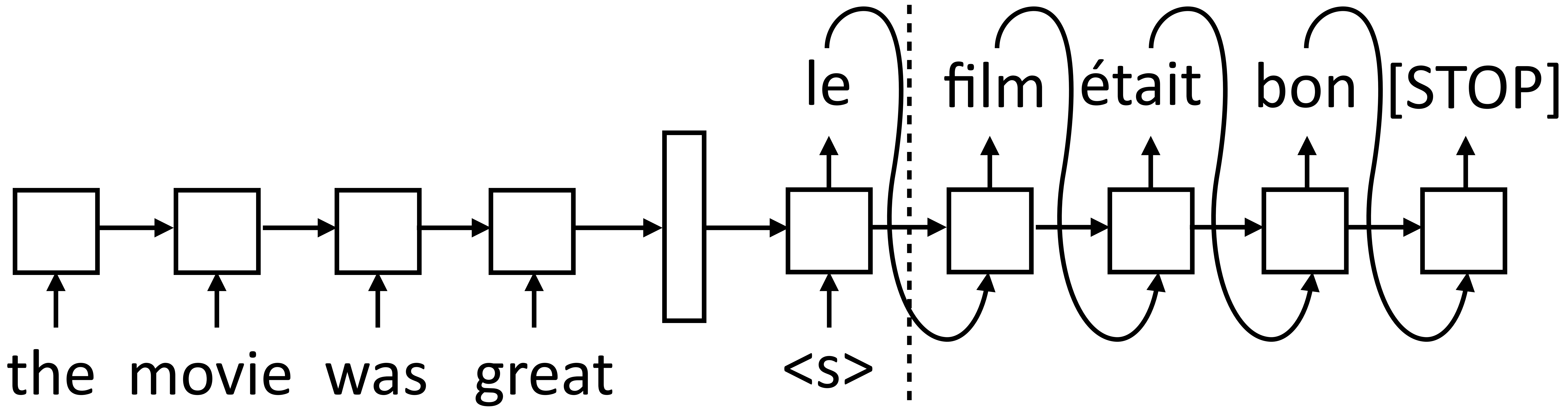

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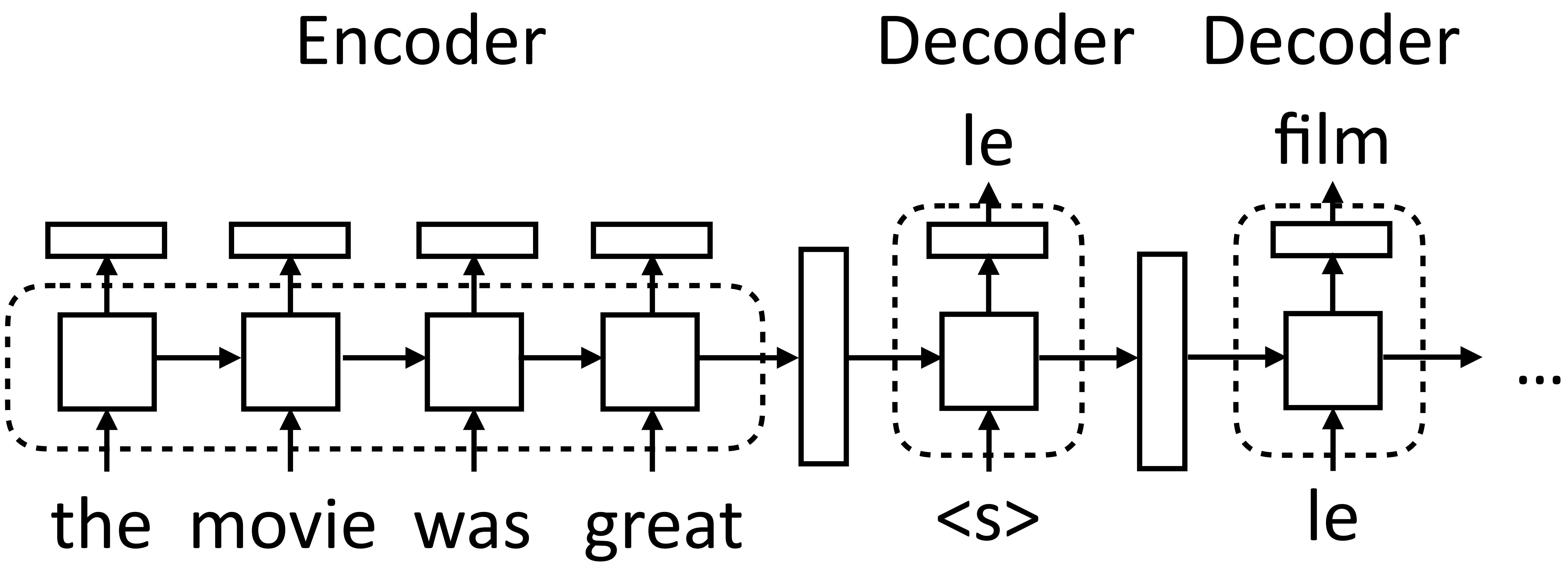
- Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models



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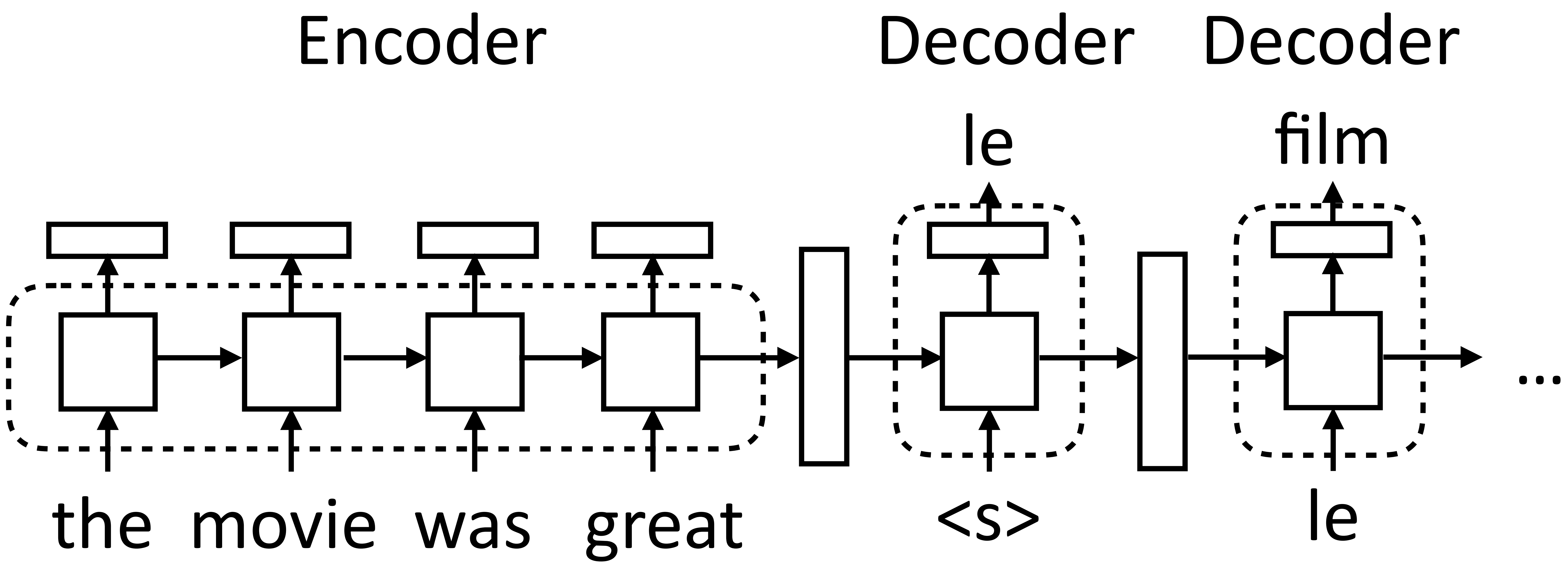

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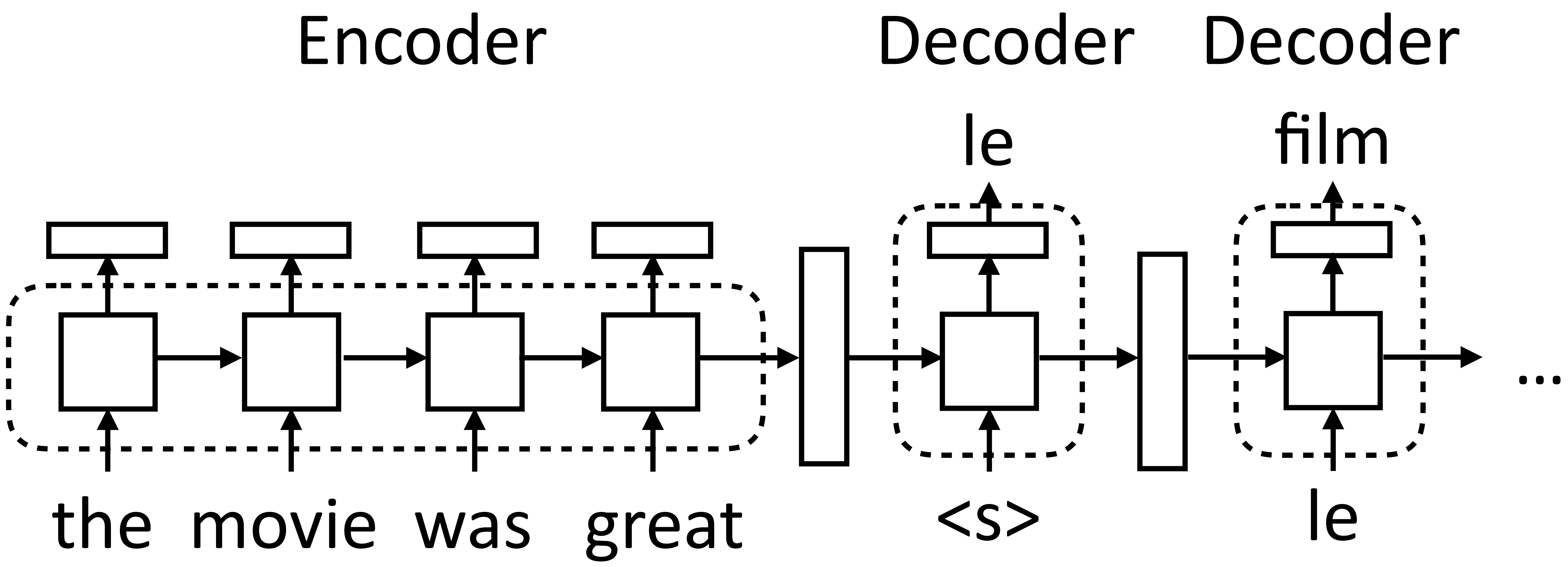
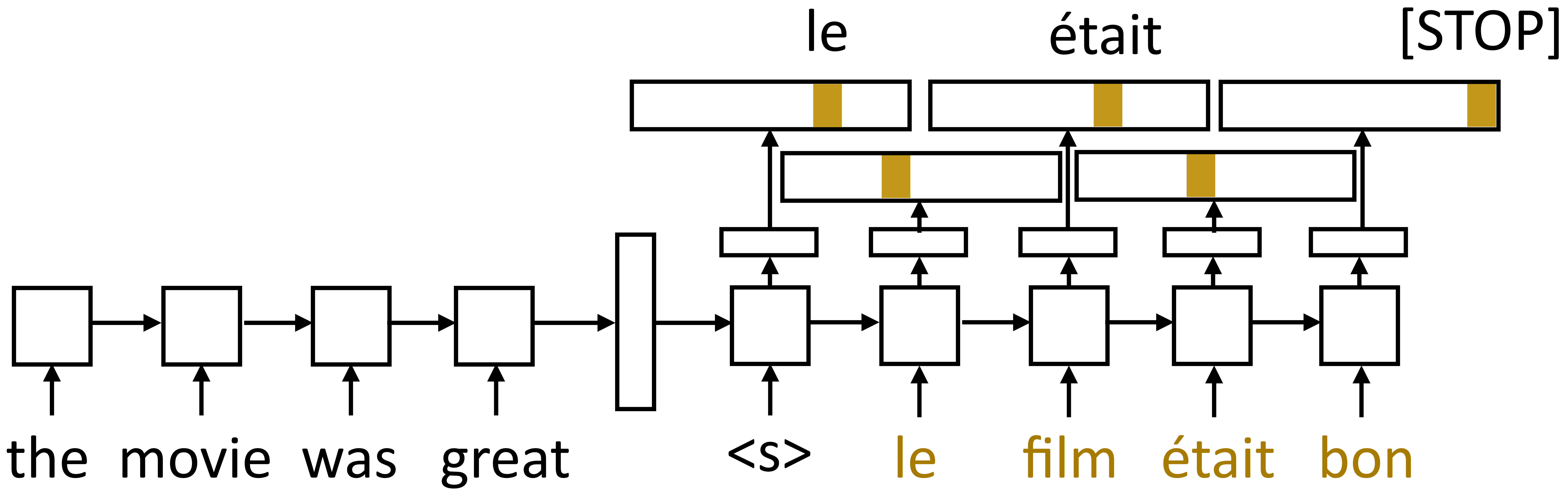


- Encoder: consumes sequence of tokens, produces a vector. Analogous to encoders for classification/tagging tasks
- Decoder: separate module, single cell. Takes two inputs: hidden state (vector *h* or tuple (*h*, *c*)) and previous token. Outputs token + new state

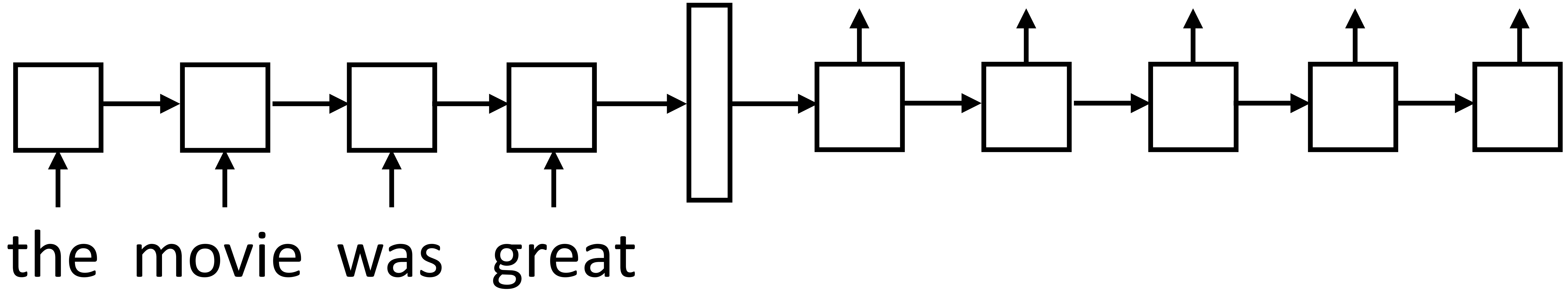
Training



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

Training: Scheduled Sampling

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



Bengio et al. (2015)

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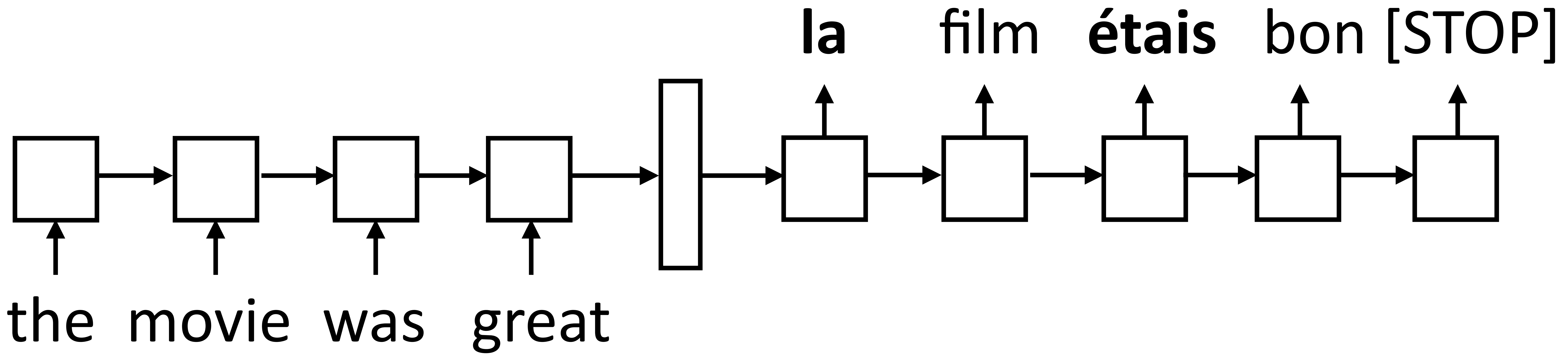

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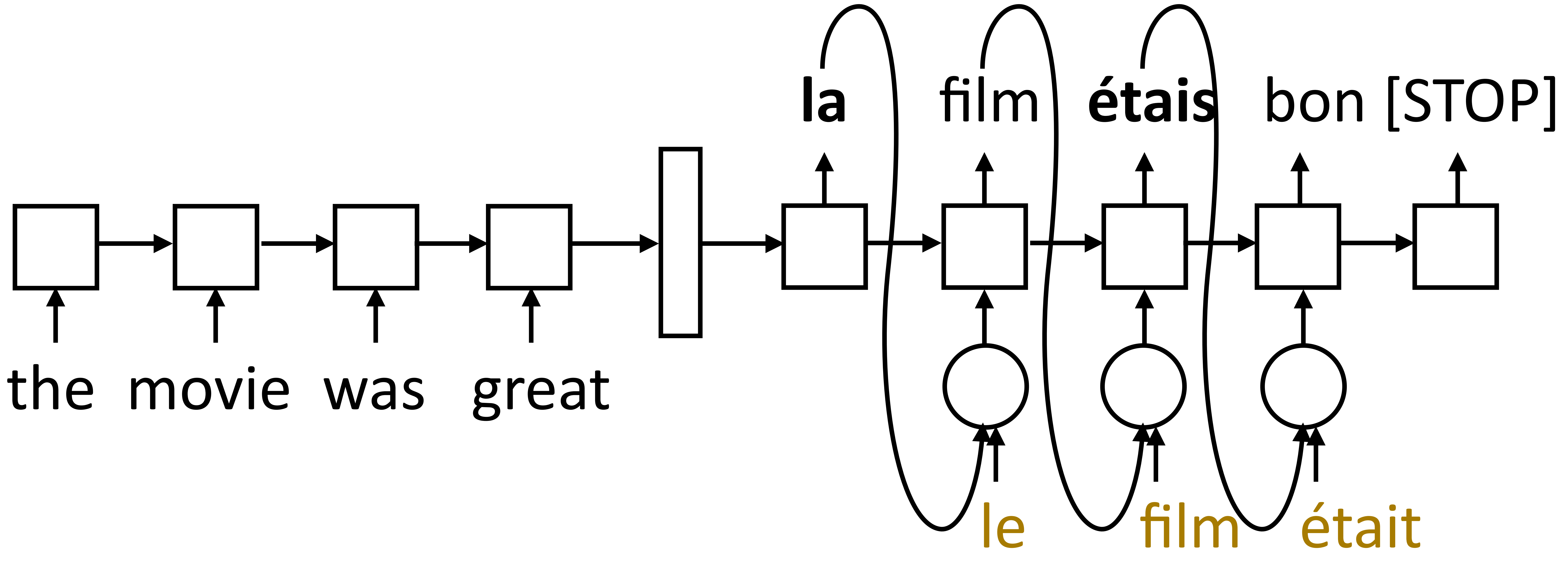

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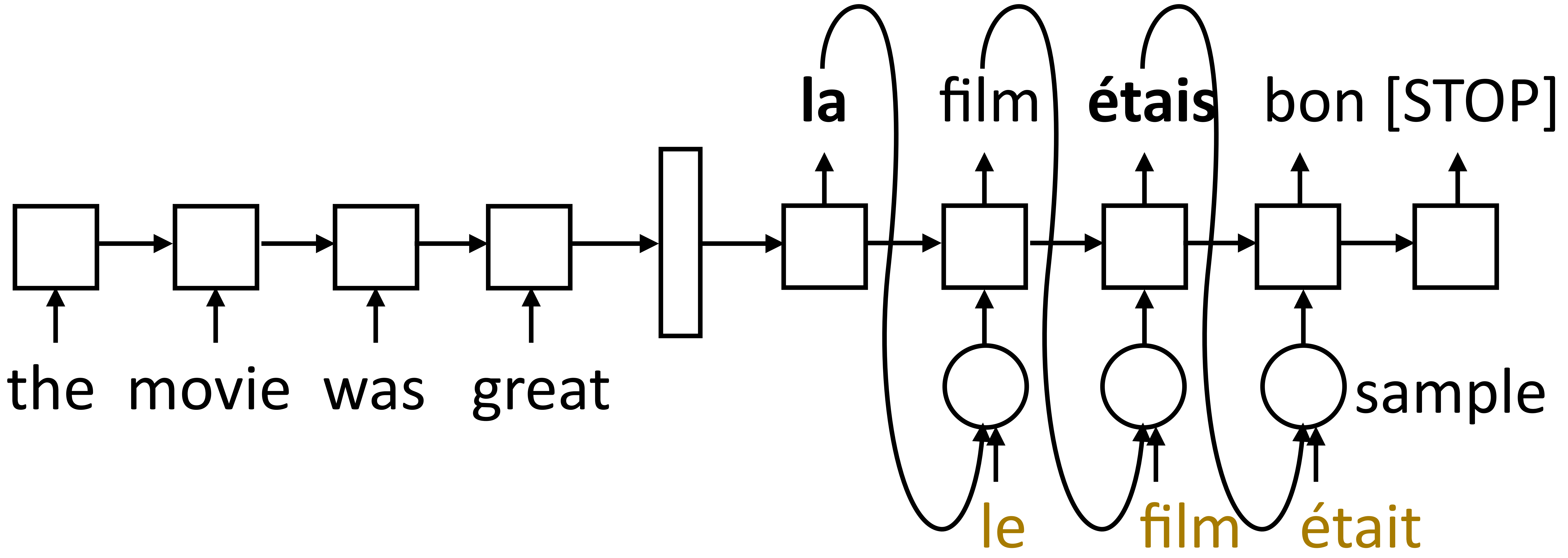

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- Starting with *p* = 1 and decaying it works best

Bengio et al. (2015)

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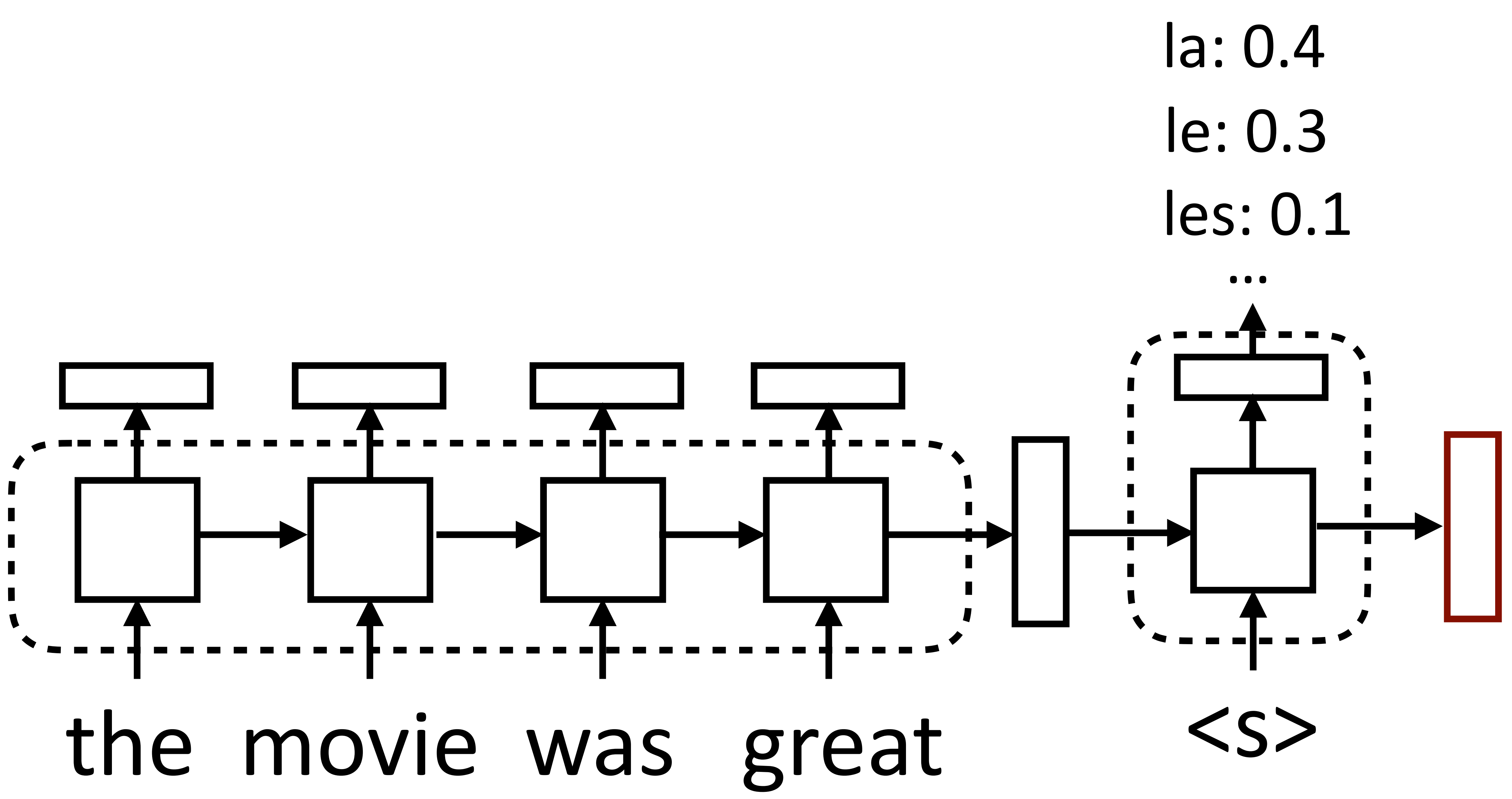
- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length
- Encoder: Can be a CNN/LSTM/…
- Decoder: also flexible in terms of architecture (more later). Execute one step of computation at a time, so computation graph is formulated as taking one input + hidden 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



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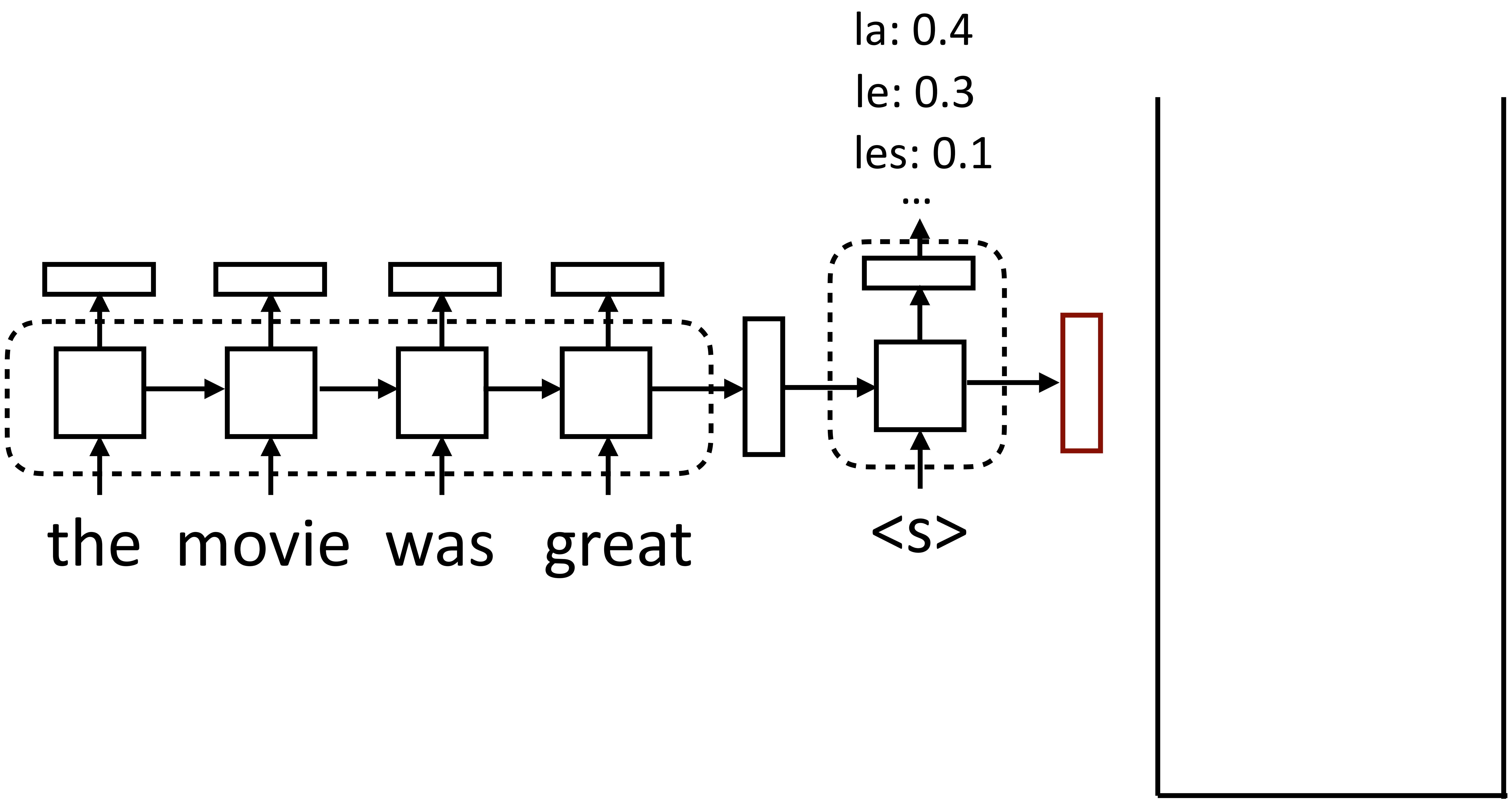

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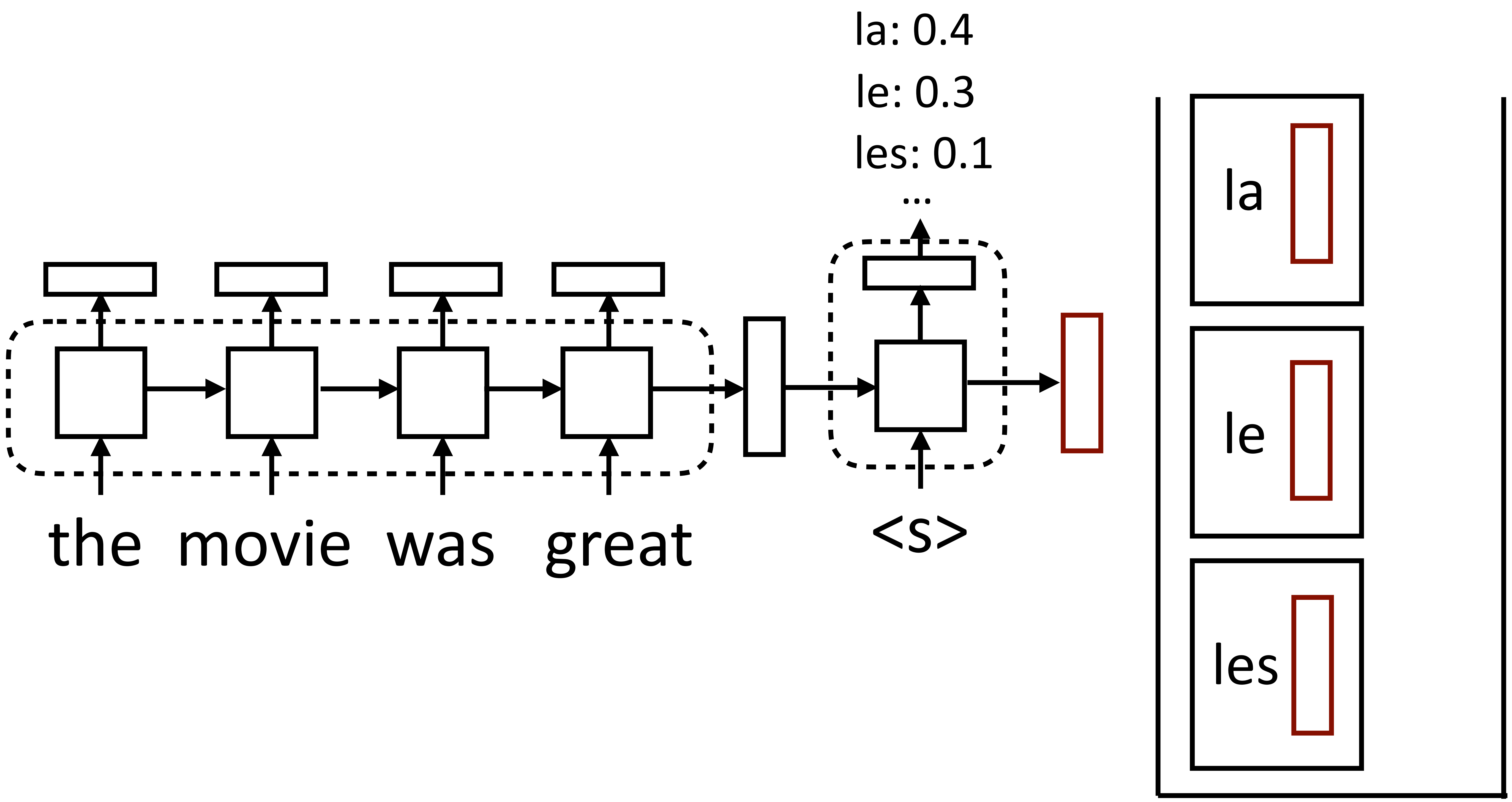

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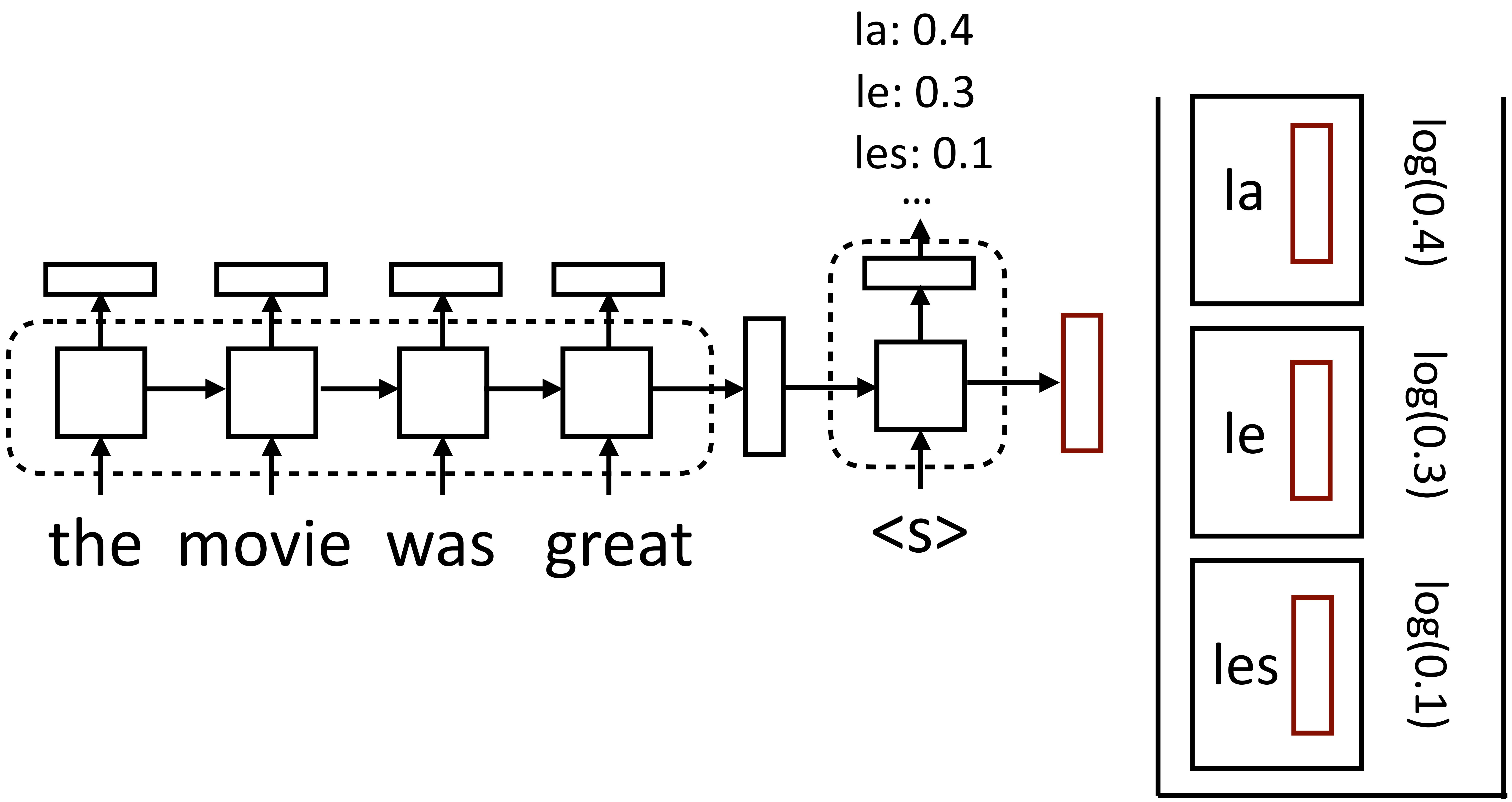

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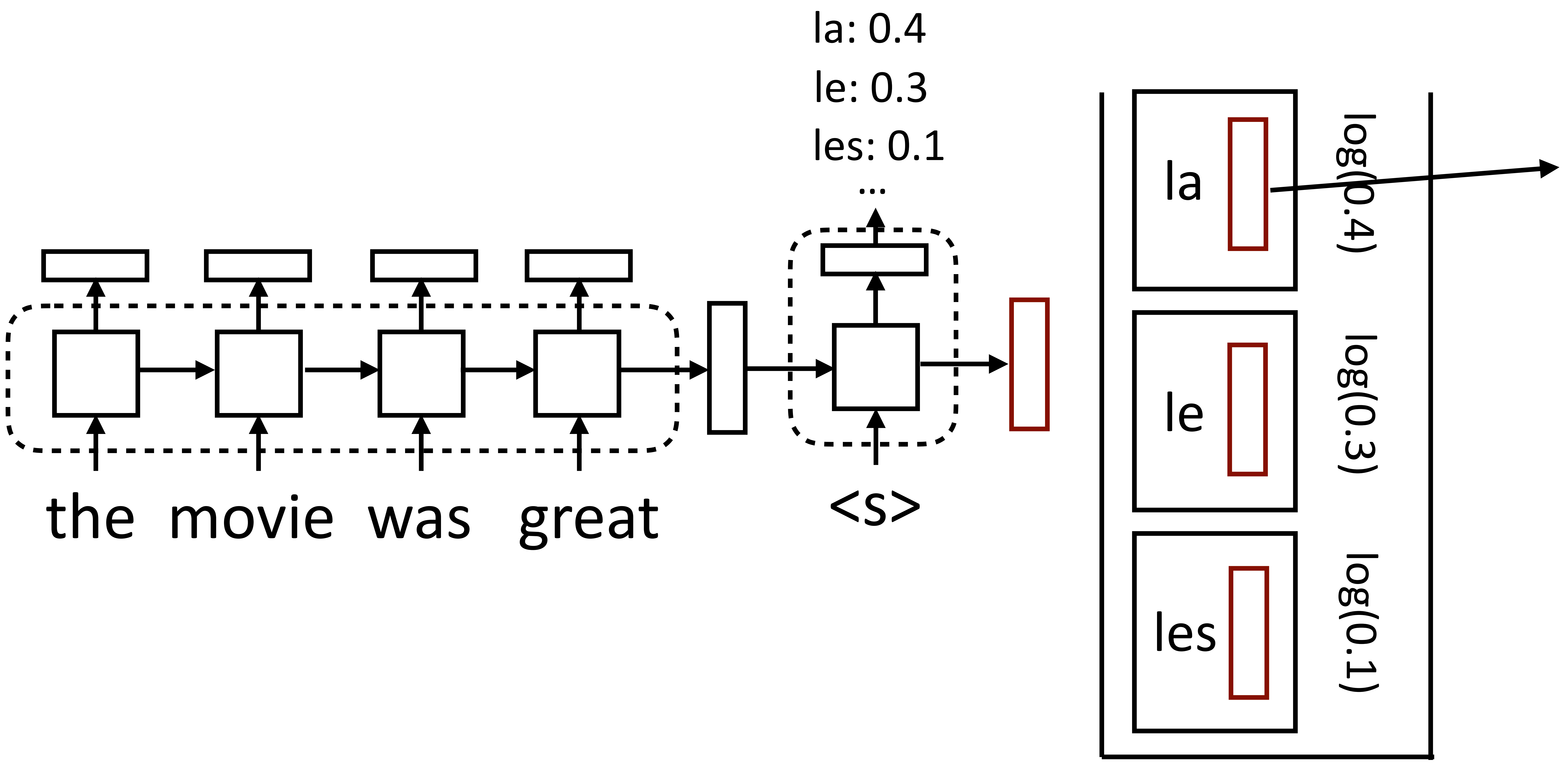

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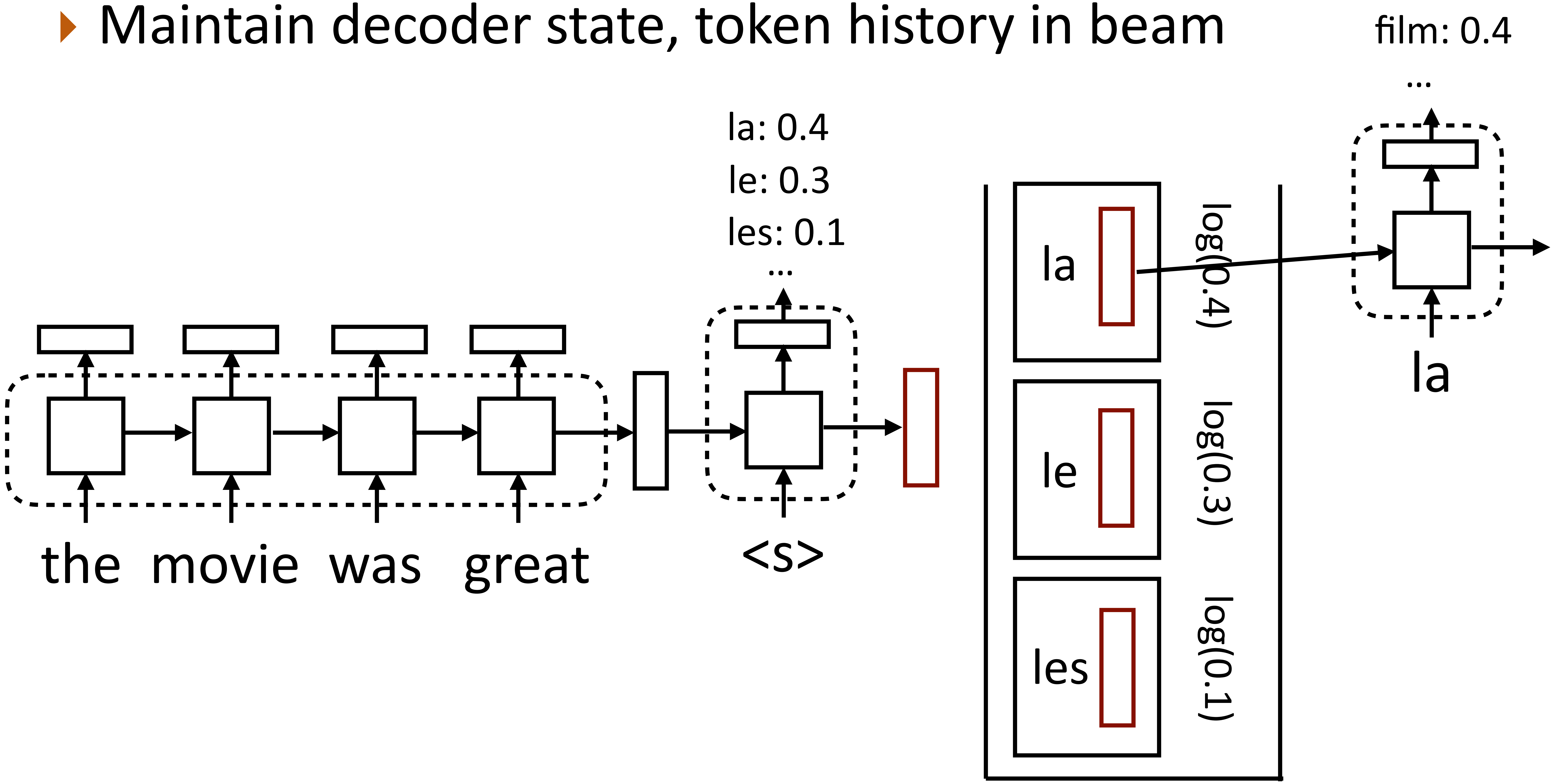

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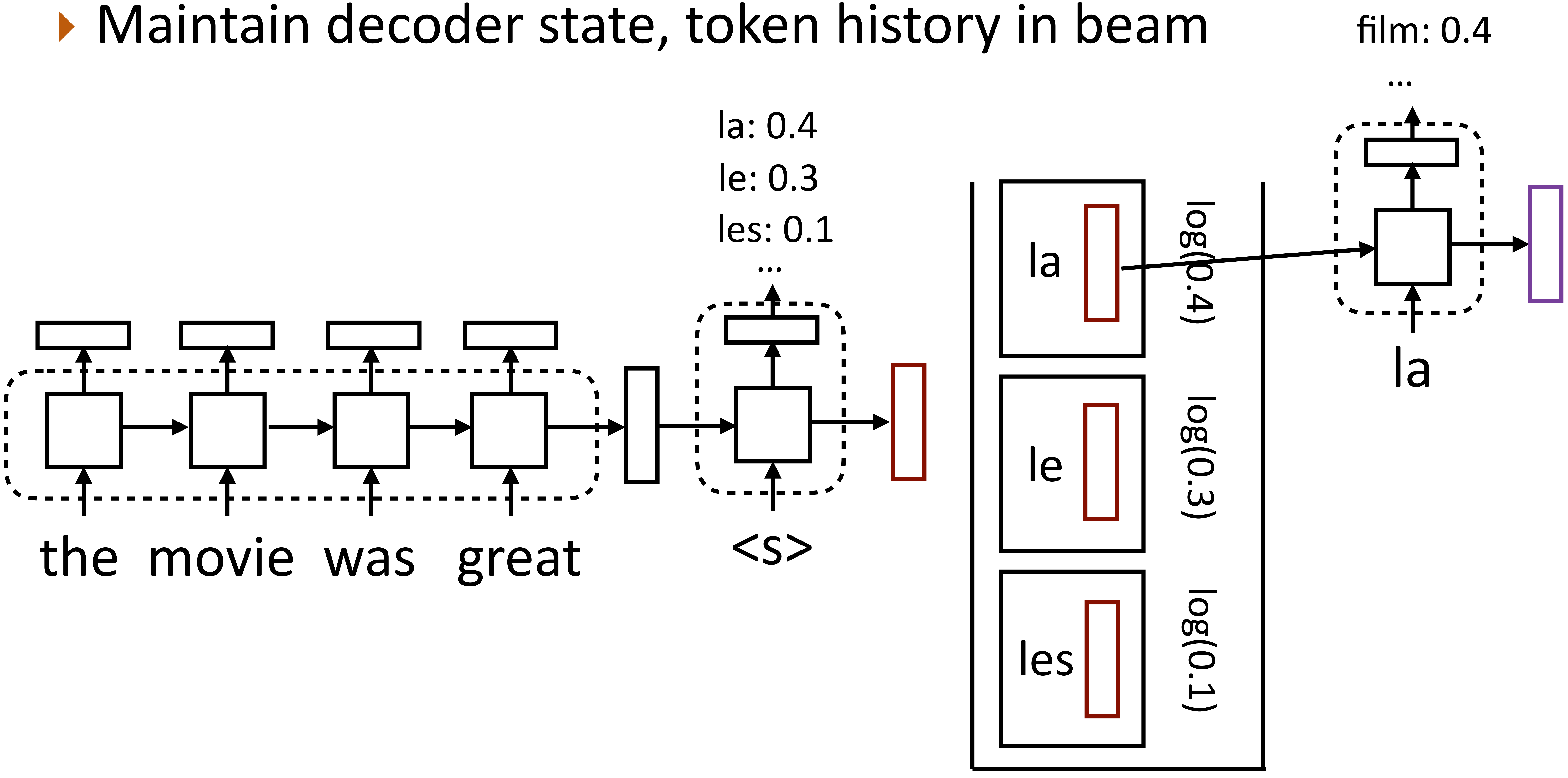

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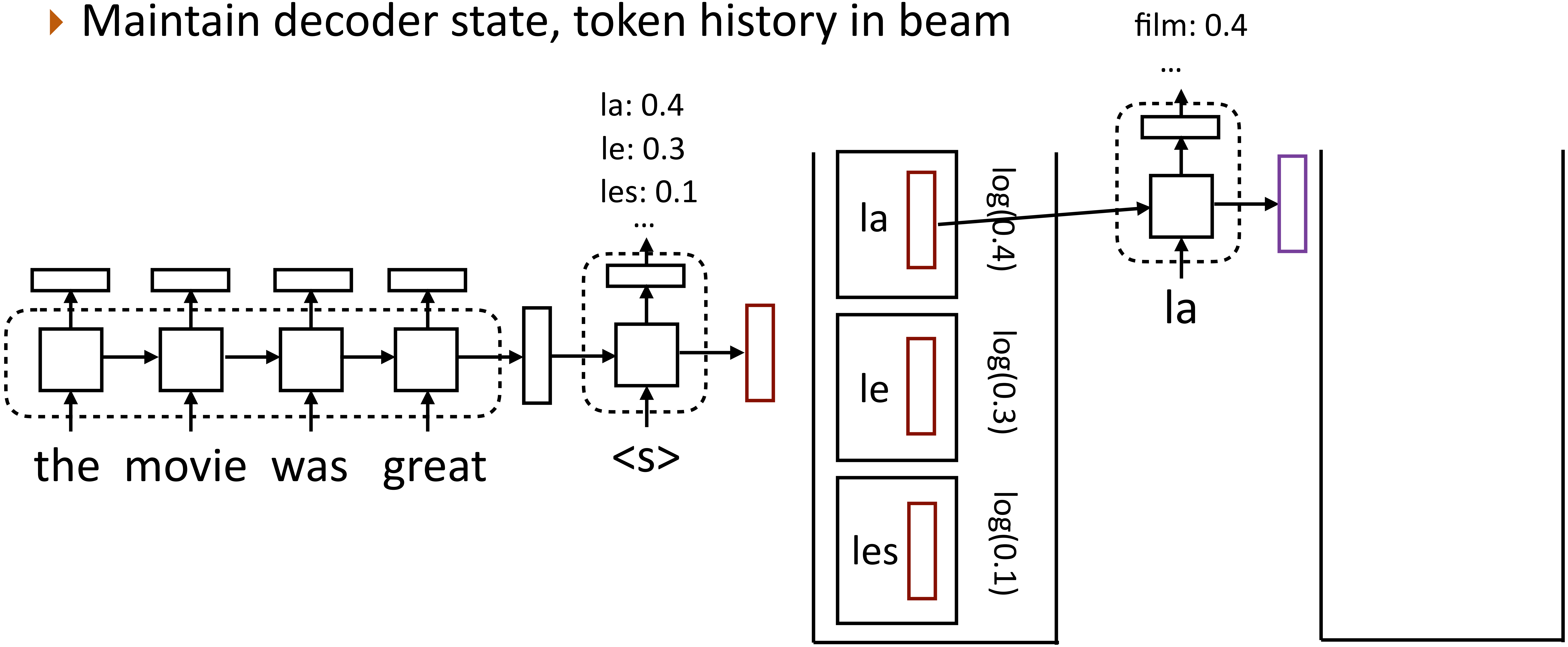

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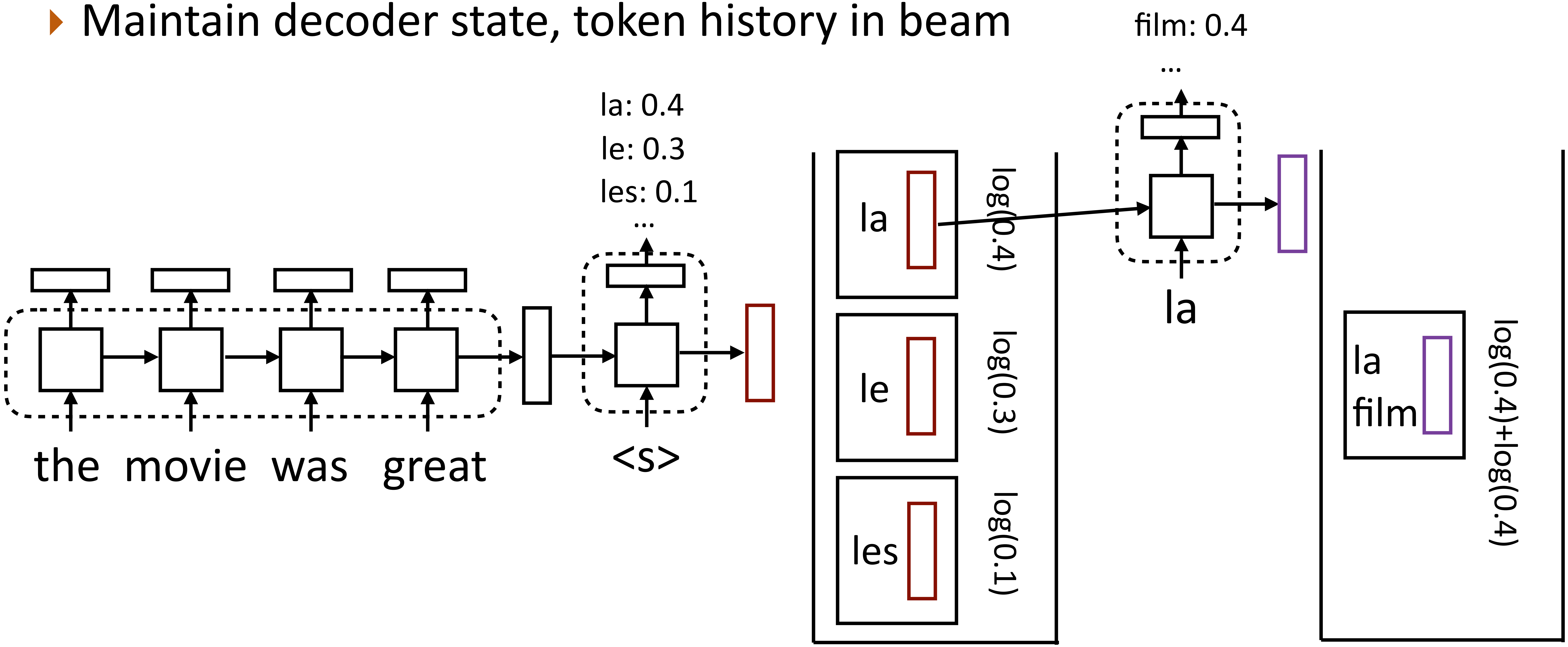

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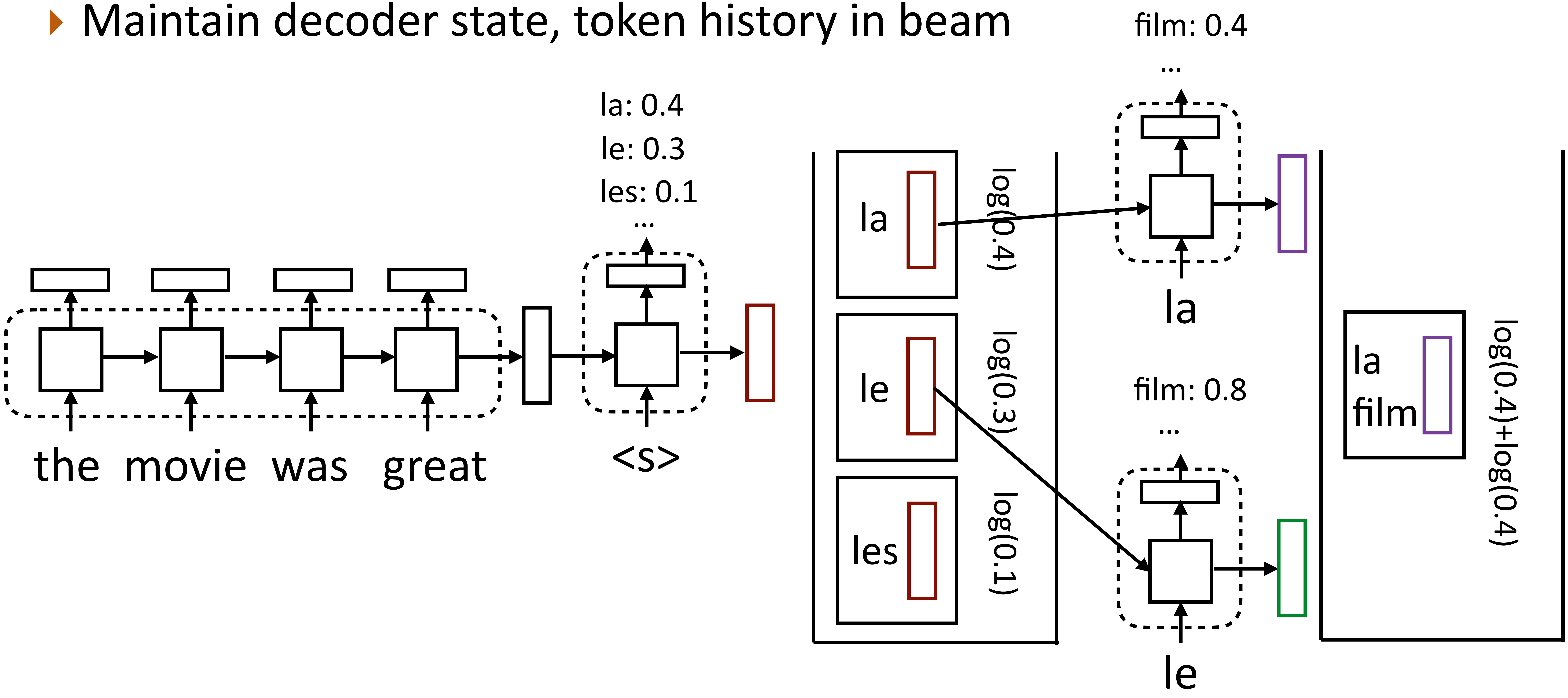

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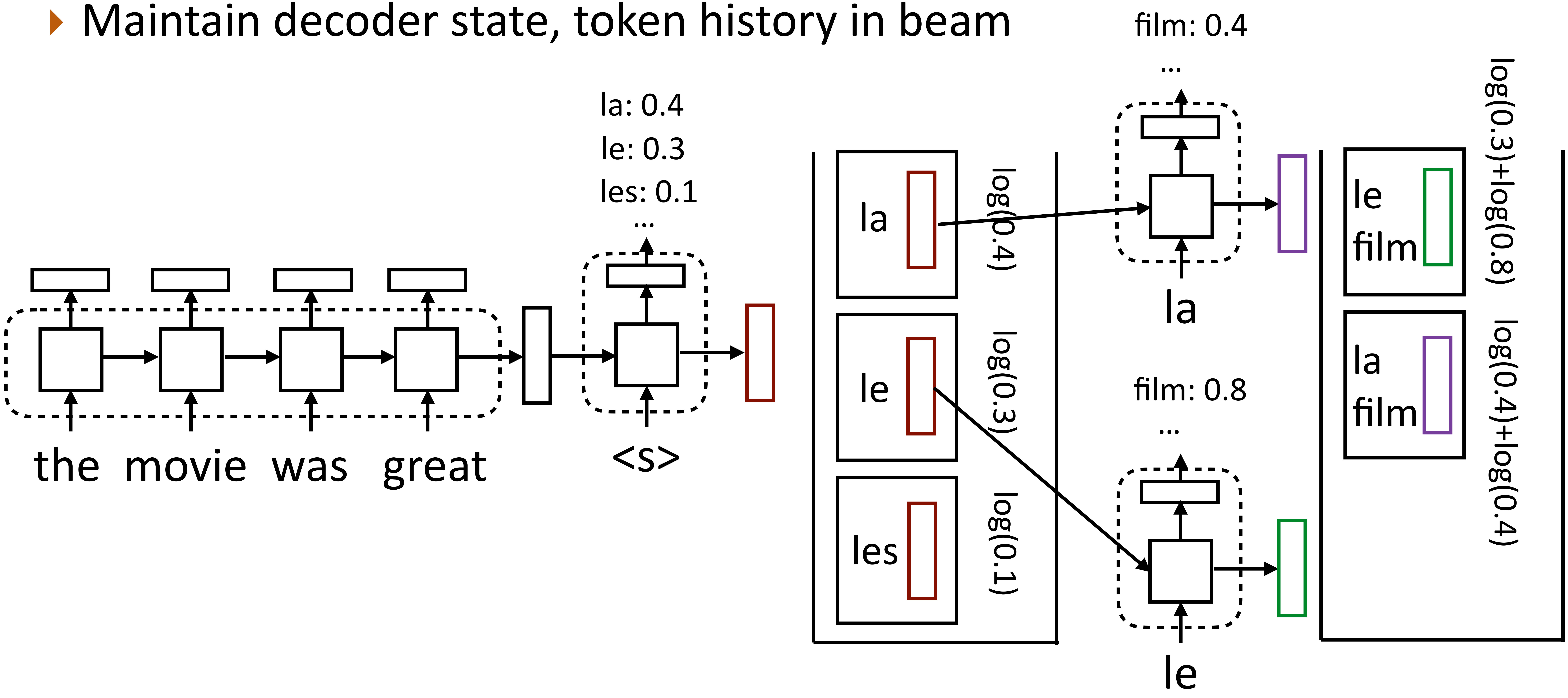

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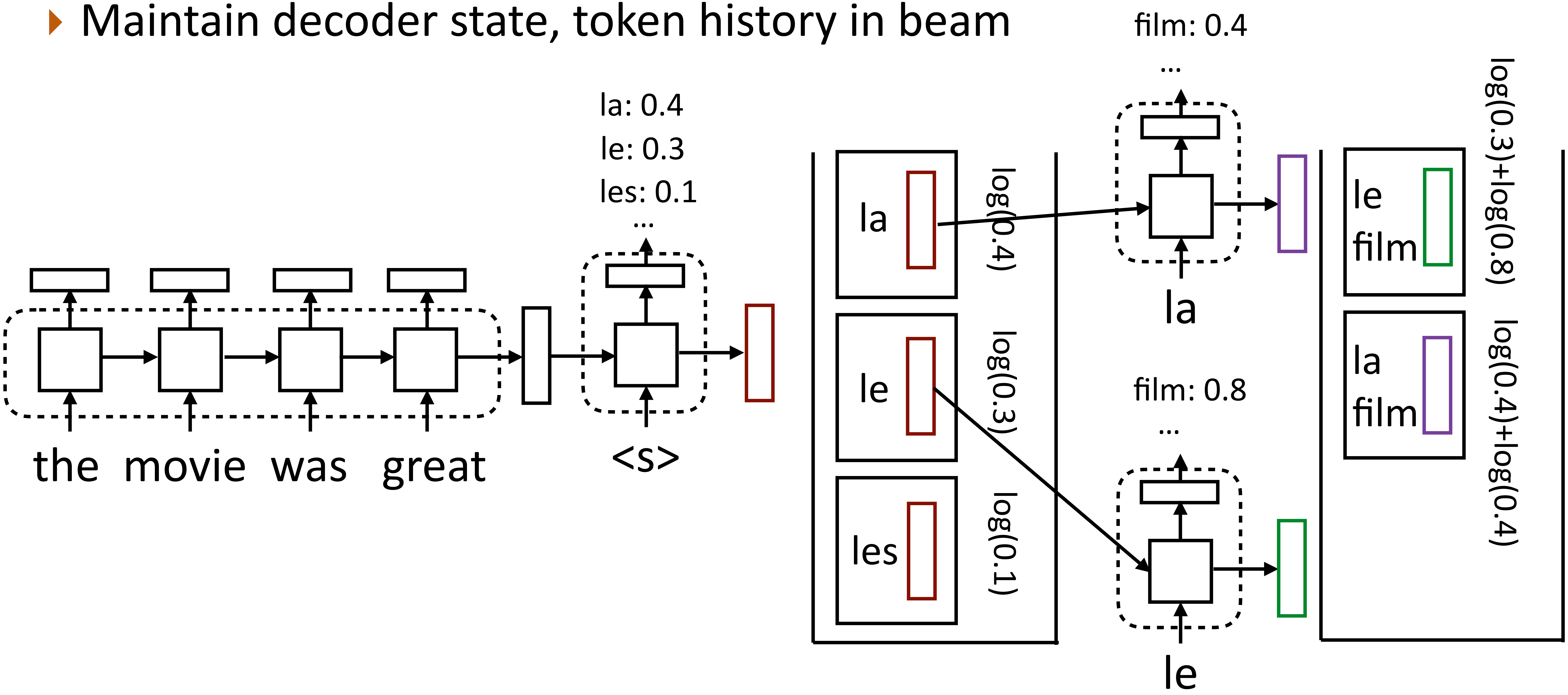

- Do **not** max over the two *film* states! Hidden state vectors are different

Semantic Parsing as Translation

"what states border Texas"

↓

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

Jia and Liang (2015)

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- No need to have an explicit grammar, simplifies algorithms
- Might not produce well-formed logical forms, might require lots of data

Jia and Liang (2015)

Regex Prediction

Locascio et al. (2016)

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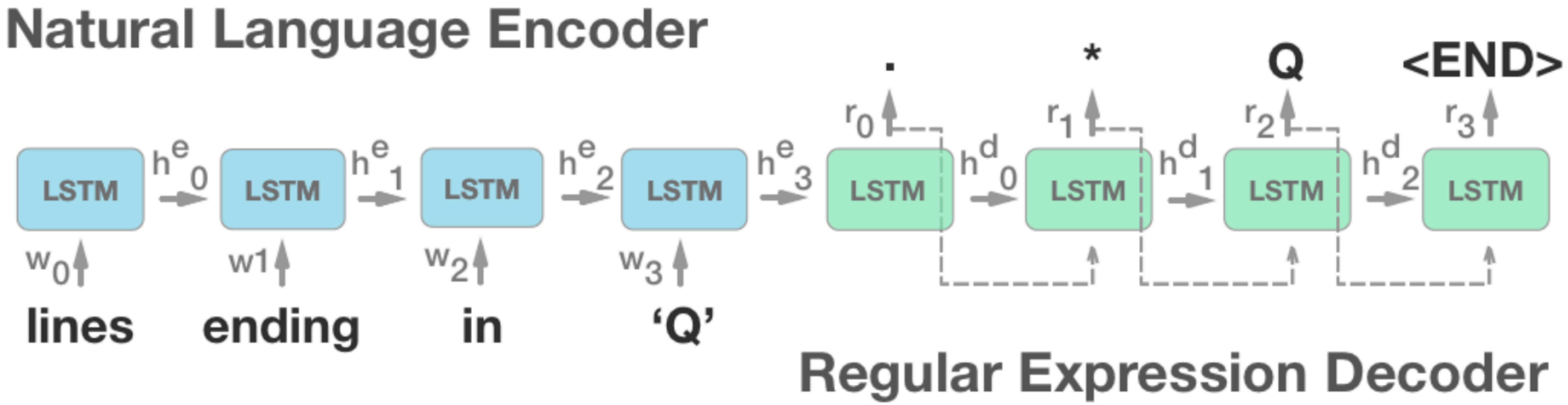

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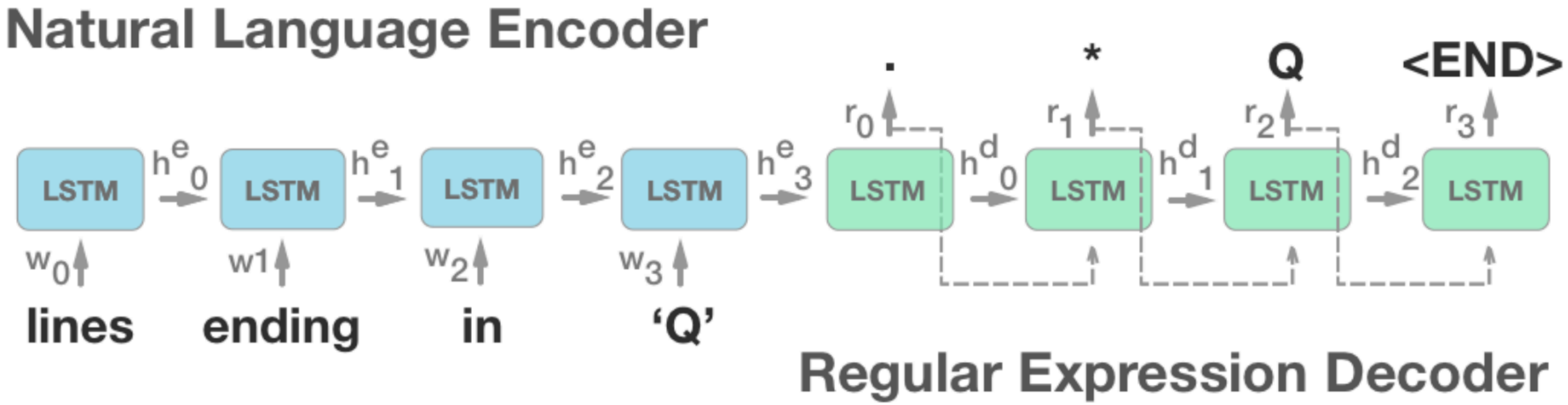

- Problem: requires a lot of data: 10,000 examples needed to get ~60% accuracy on pretty simple regexes

Locascio et al. (2016)

SQL Generation

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

Question:

How many CFL teams are from York College?

SQL:

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

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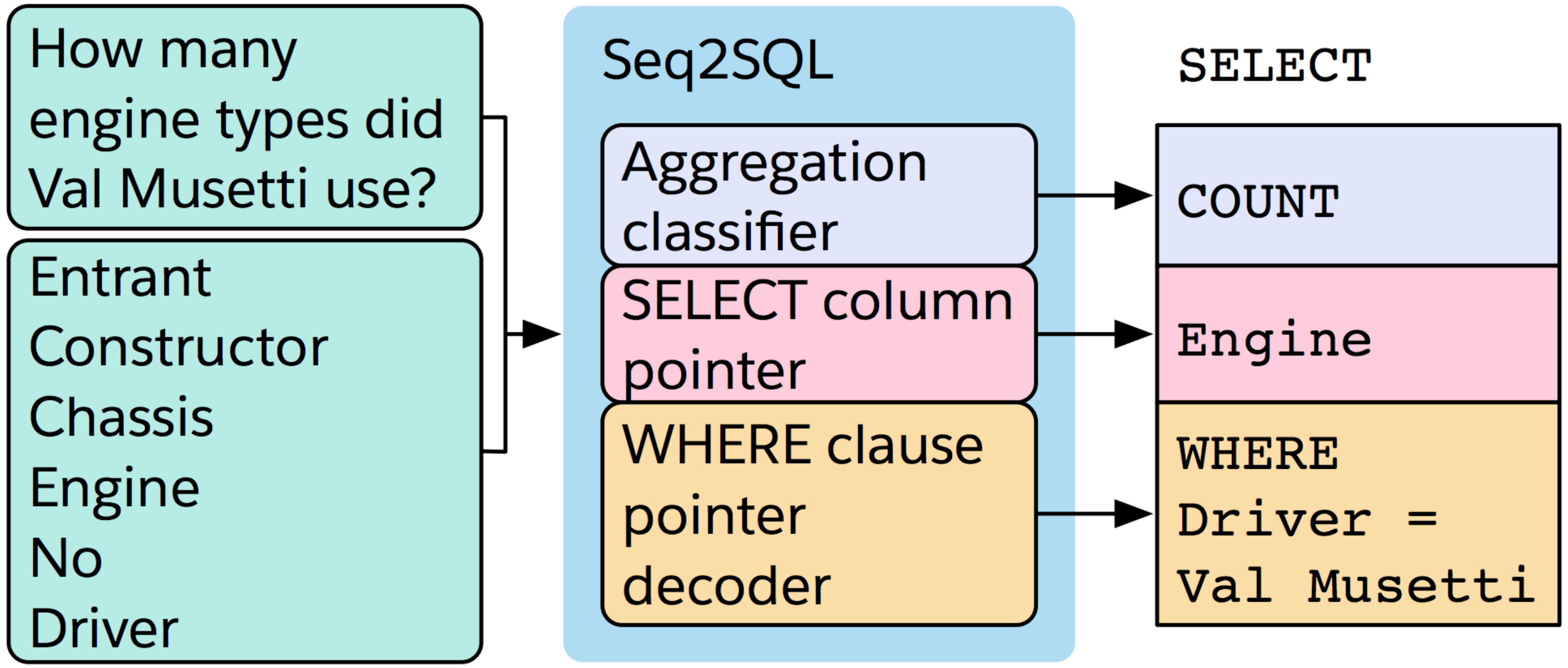

Zhong et al. (2017)

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

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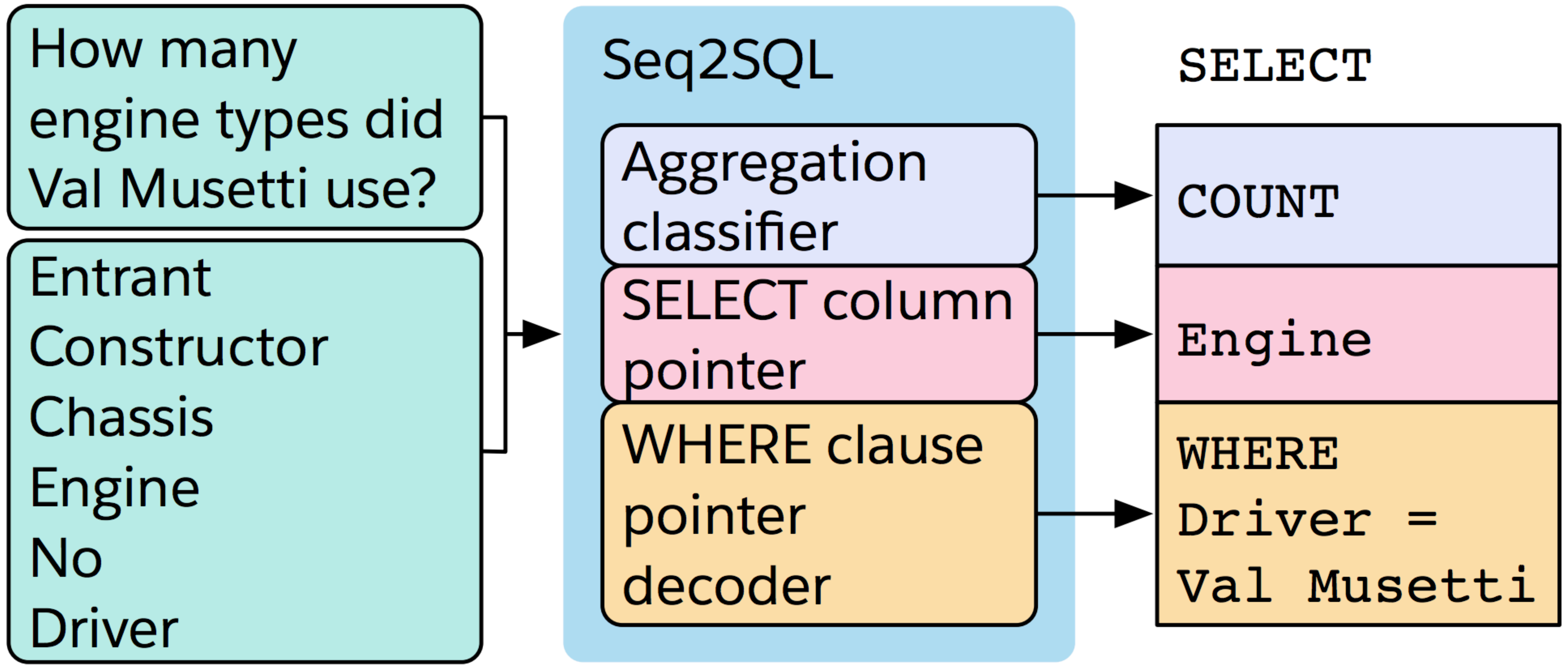

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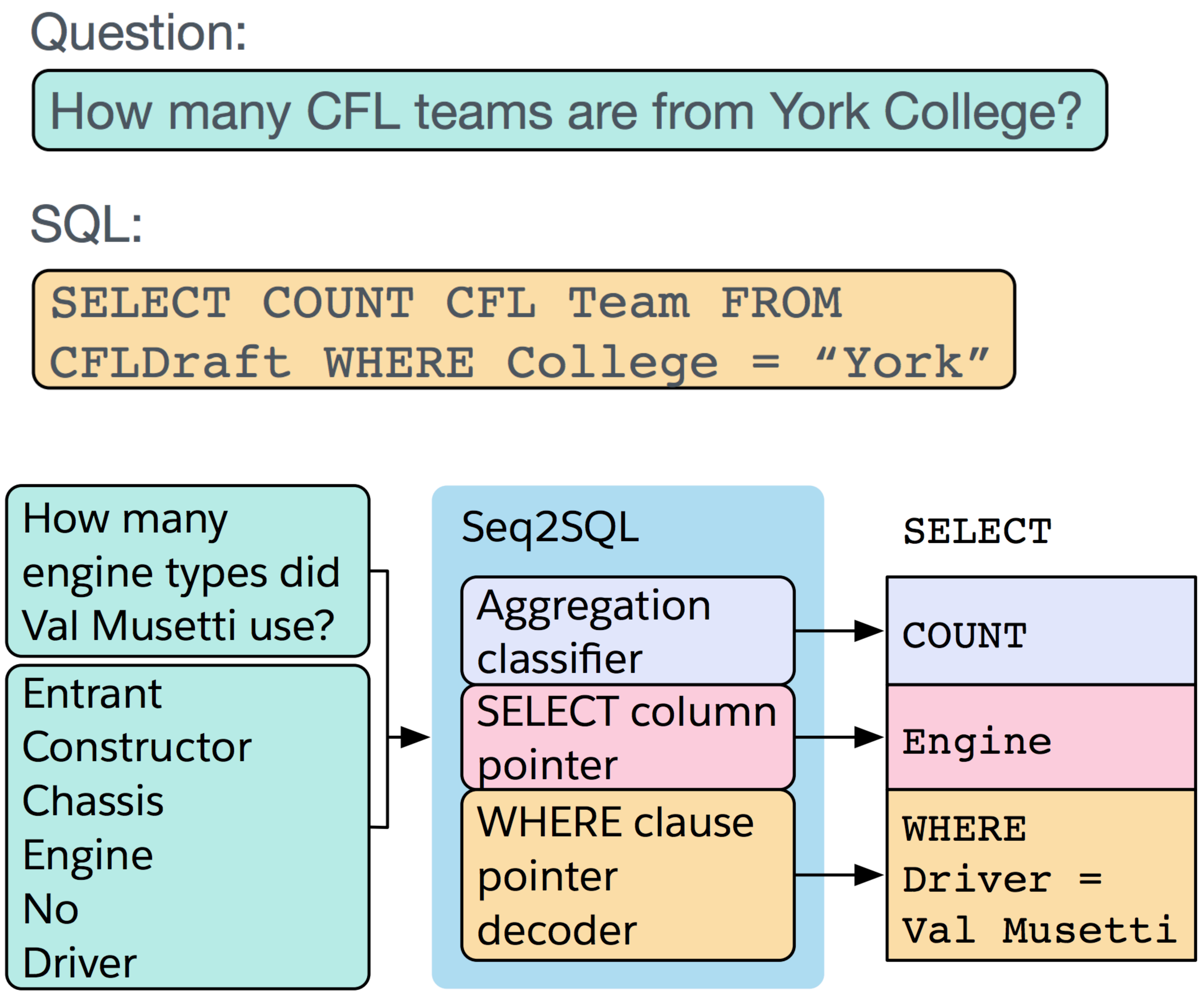

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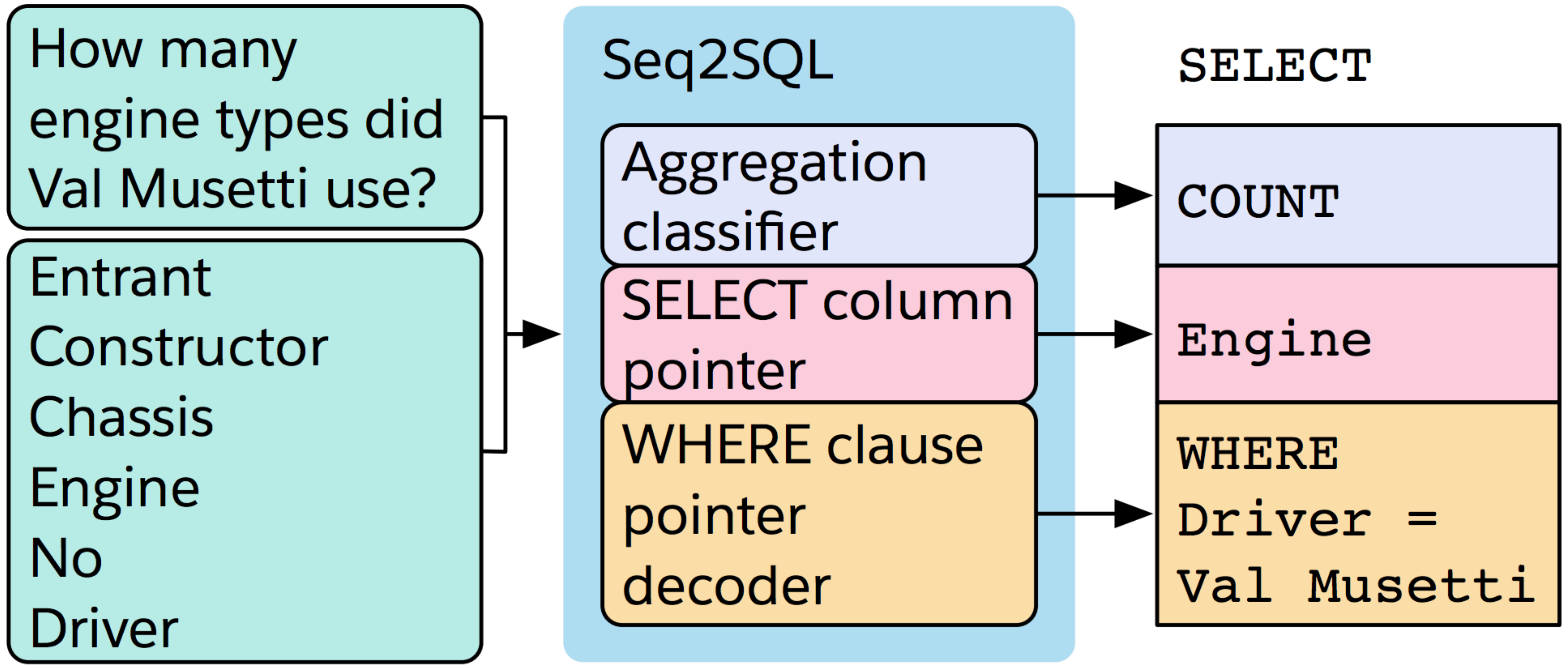

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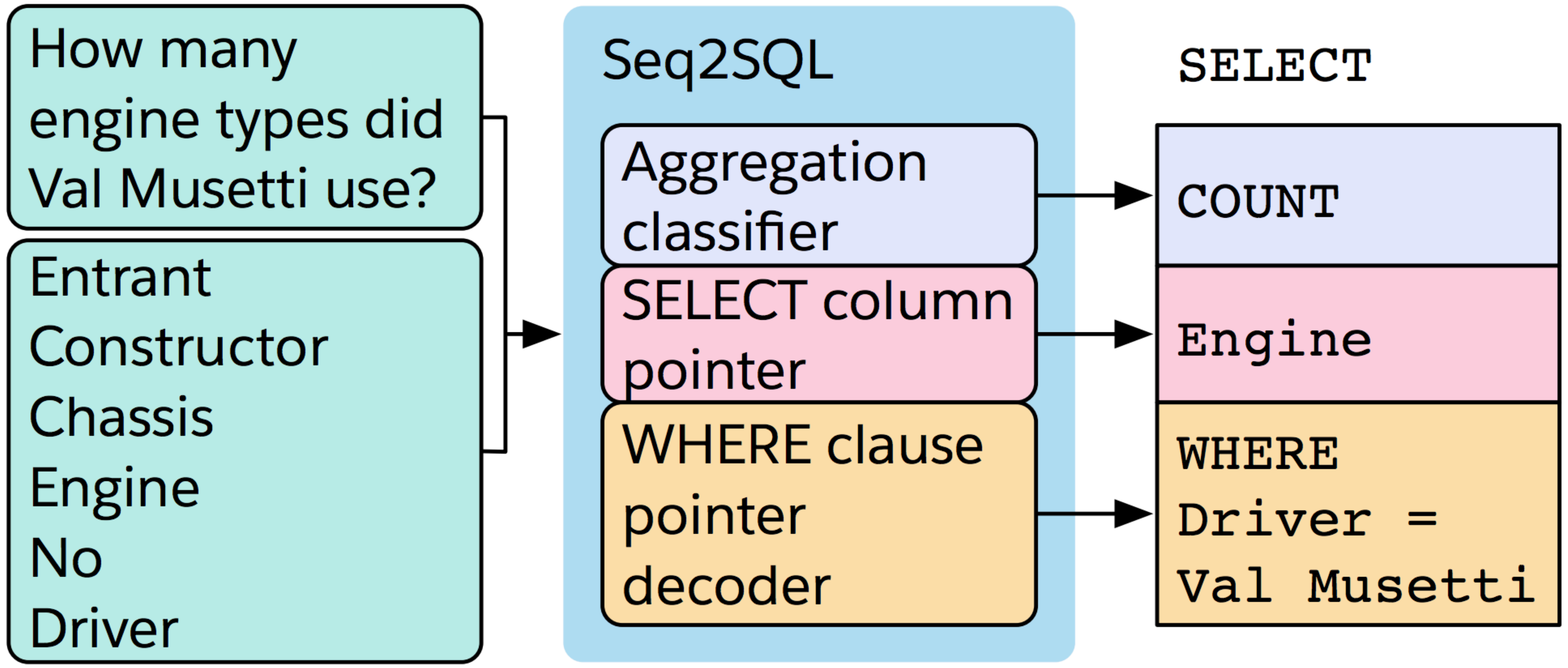

Zhong et al. (2017)

Attention

Problems with Seq2seq Models

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- Often a byproduct of training these models poorly

- Need some notion of input coverage or what input words we've translated

Problems with Seq2seq Models

- Unknown words:

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

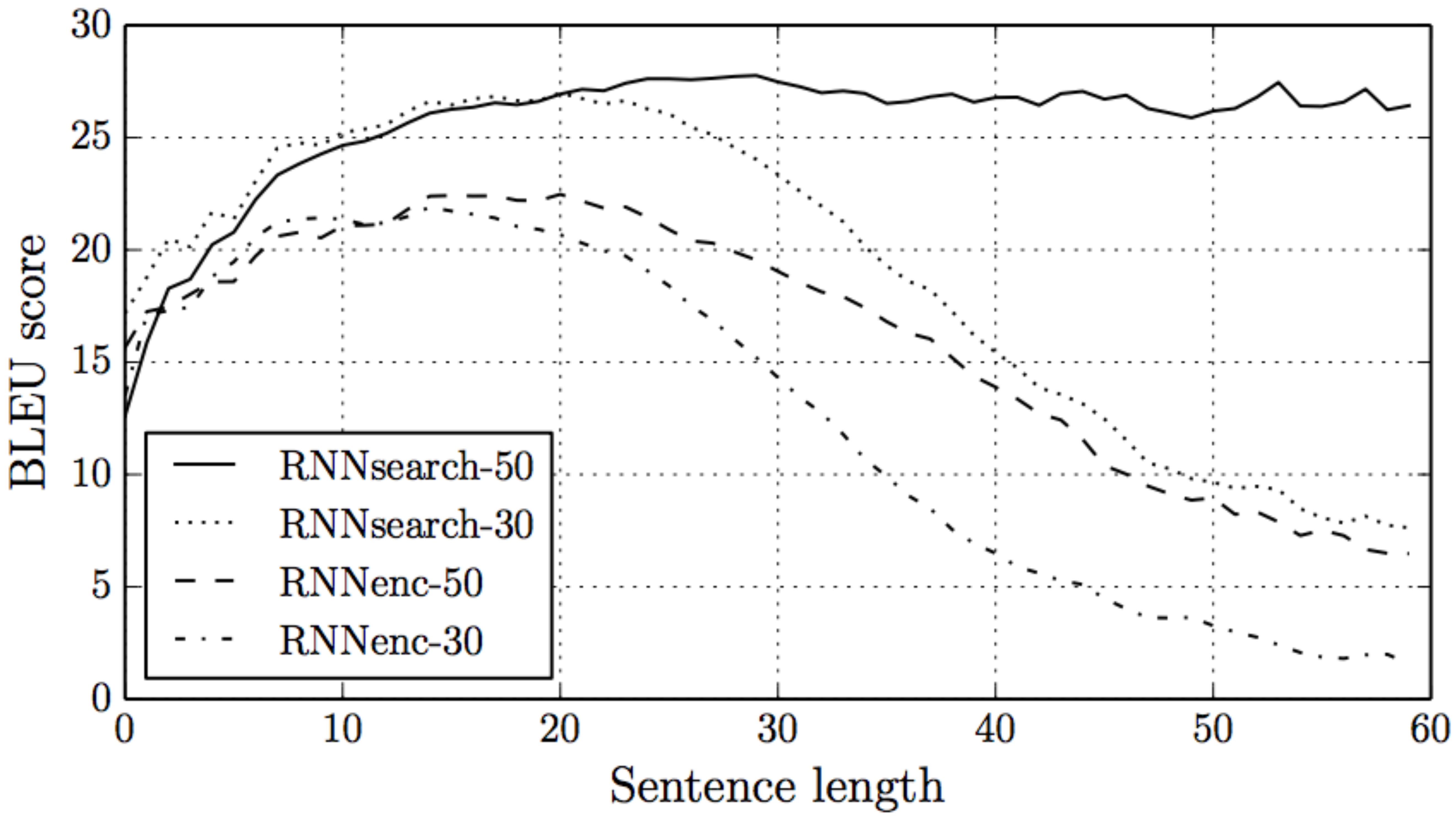
fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] . . . , a été *démonté* jeudi matin

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

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

Problems with Seq2seq Models

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



RNNsearch: introduces attention mechanism to give "variable-sized" representation

Bahdanau et al. (2014)

Aligned Inputs

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

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

the movie was great

le film était bon

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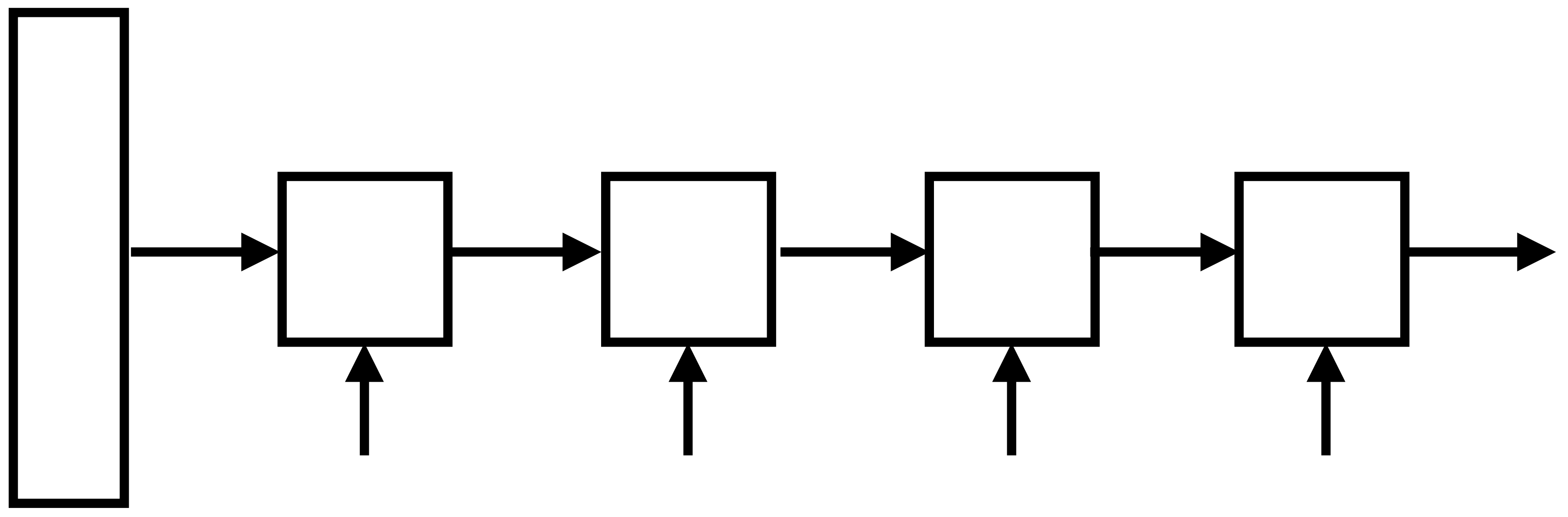

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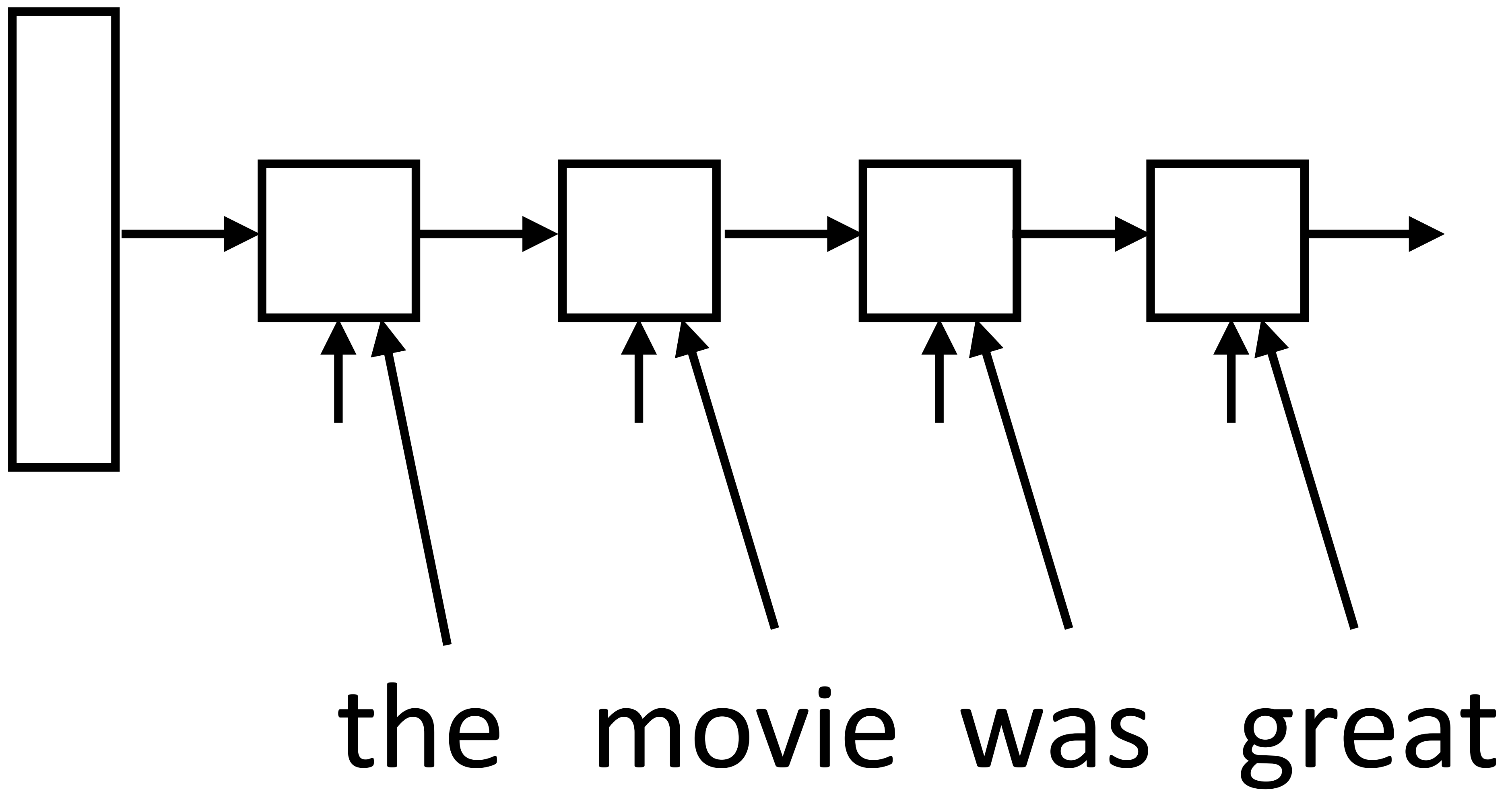

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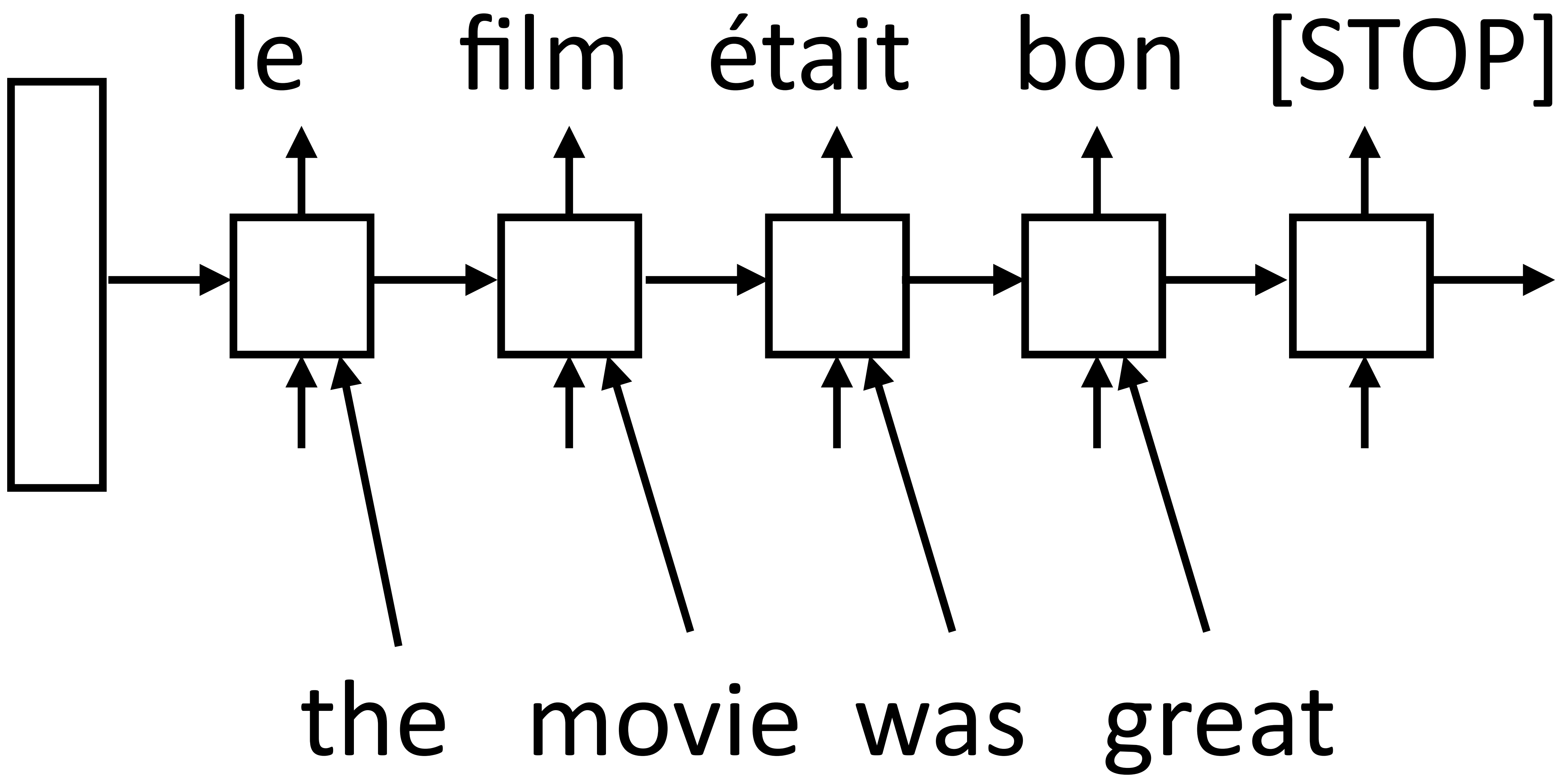

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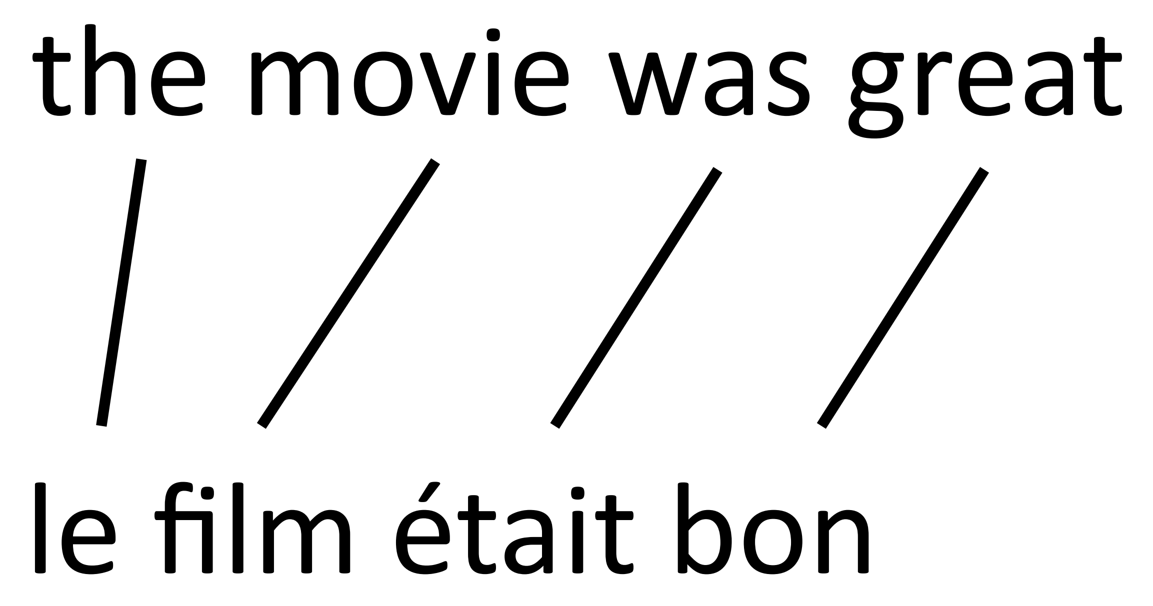

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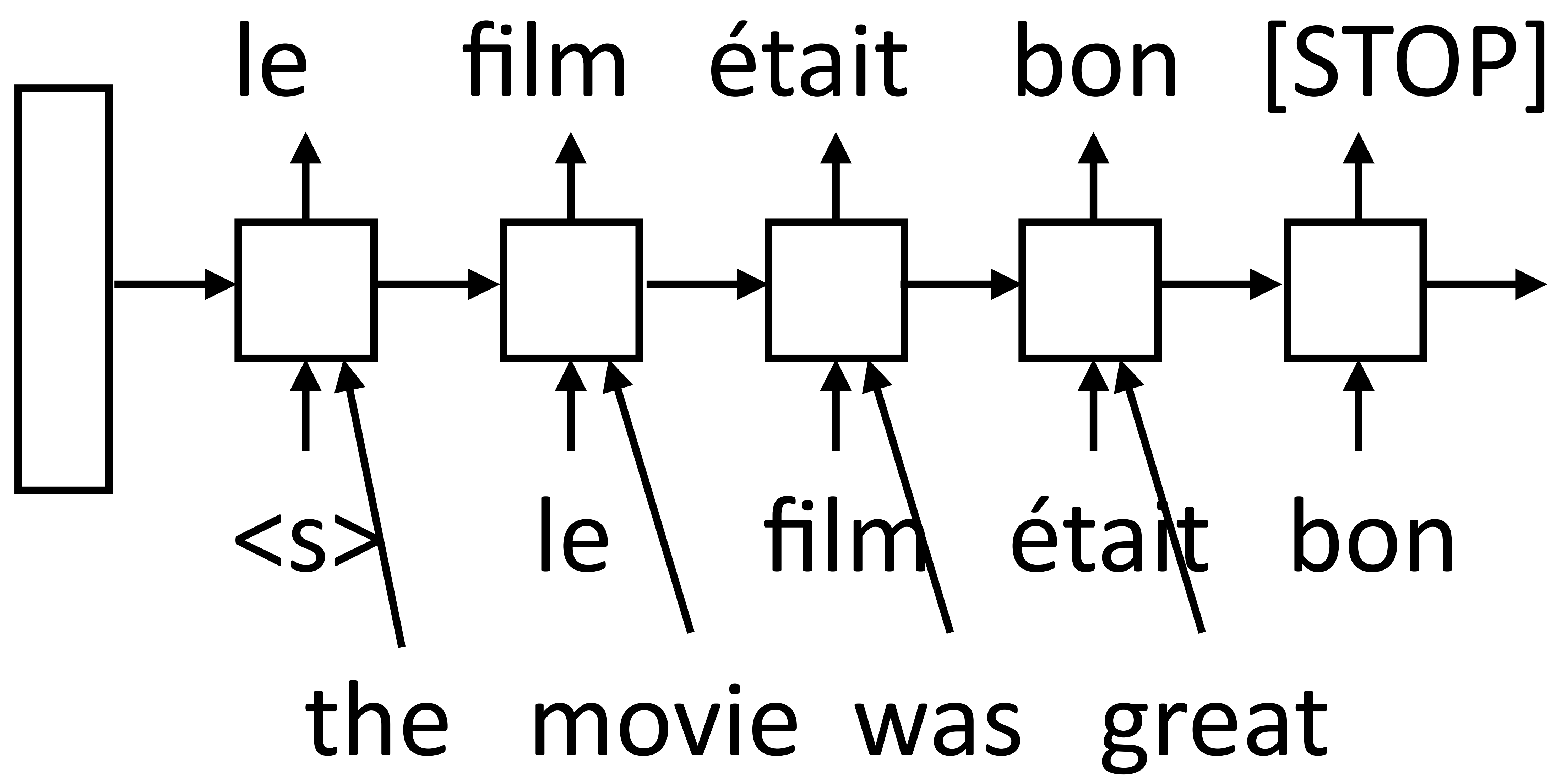

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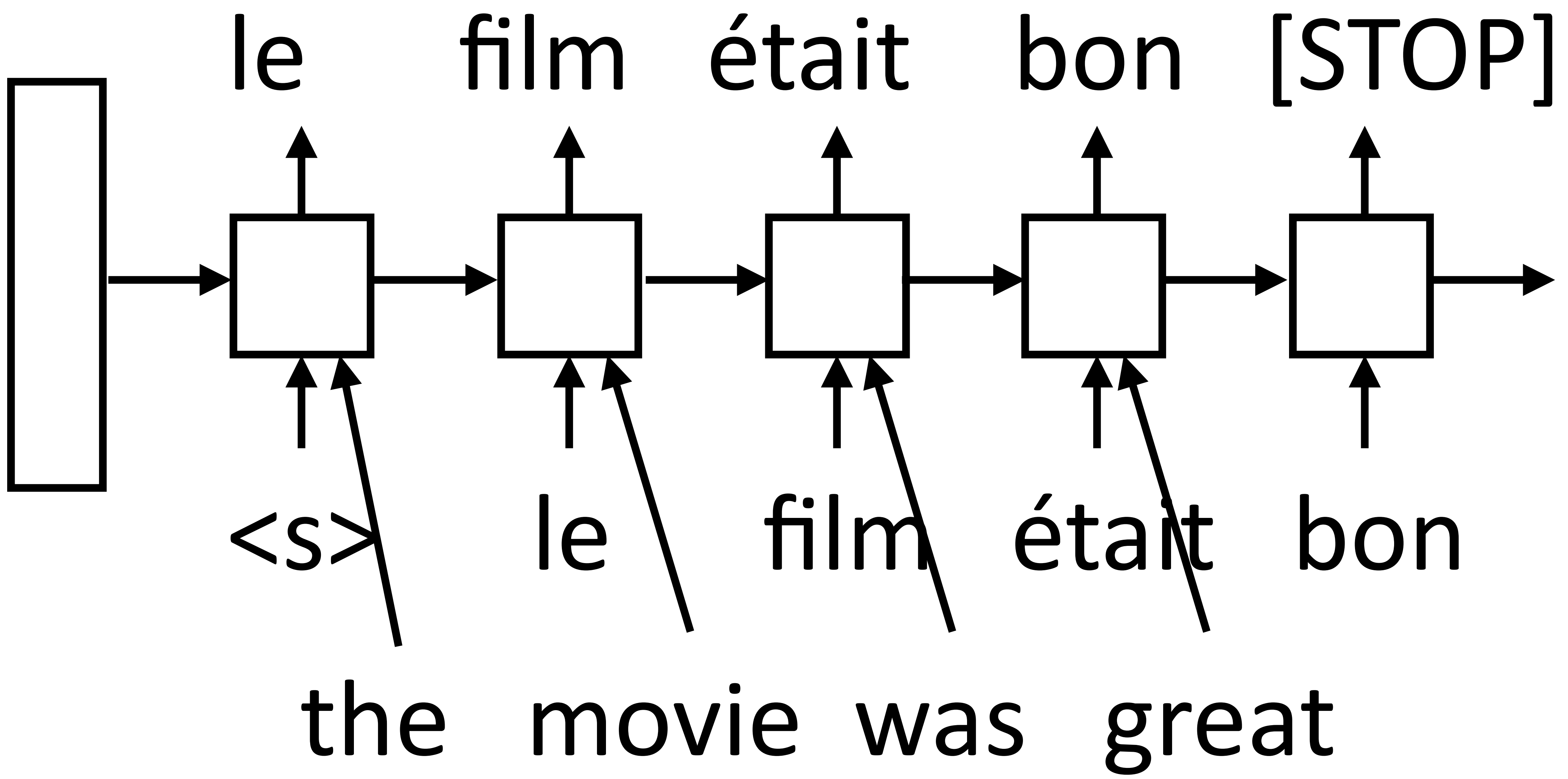

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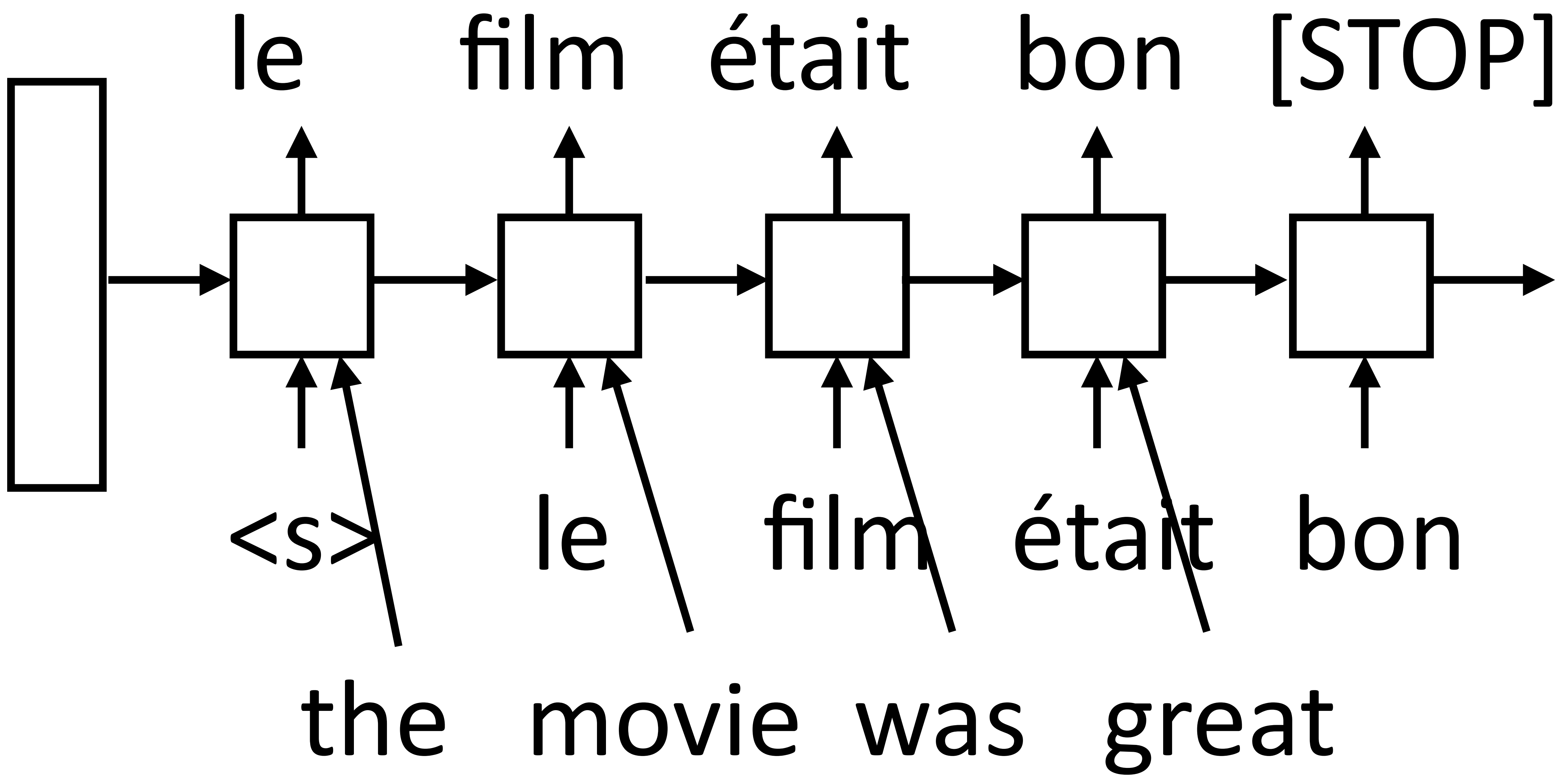
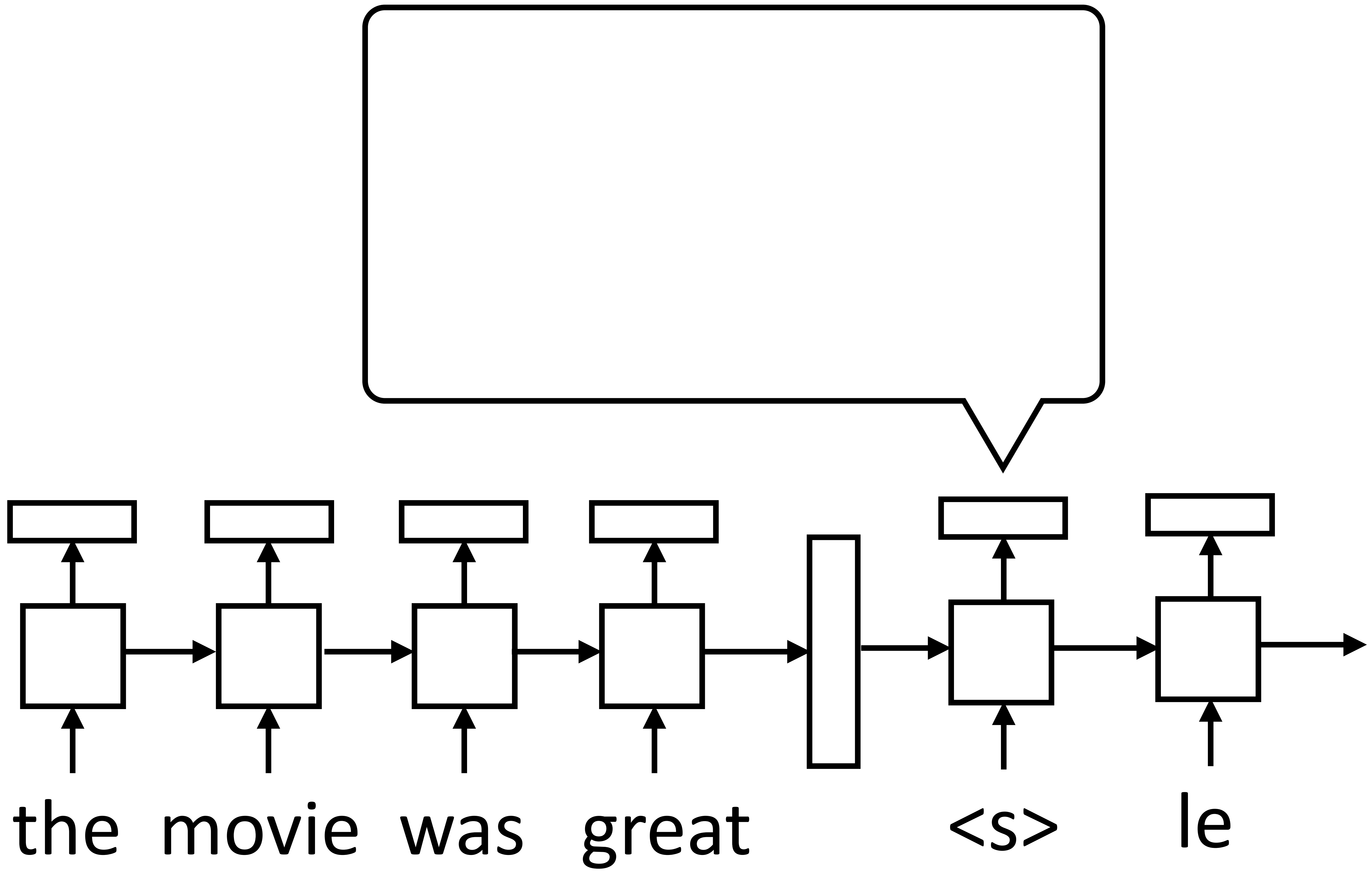


- Much less burden on the hidden state

- How can we achieve this without hardcoding it?

Attention



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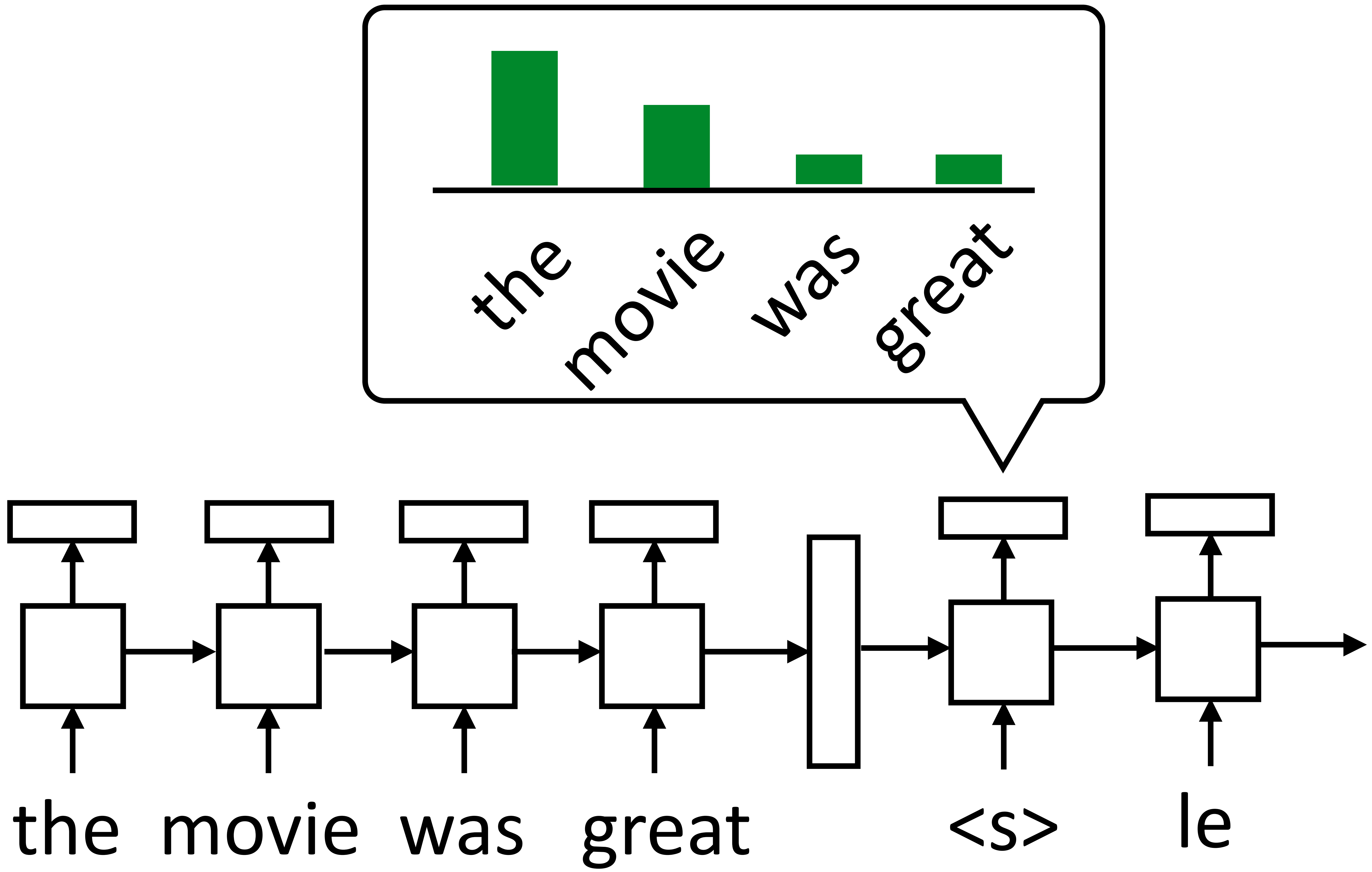

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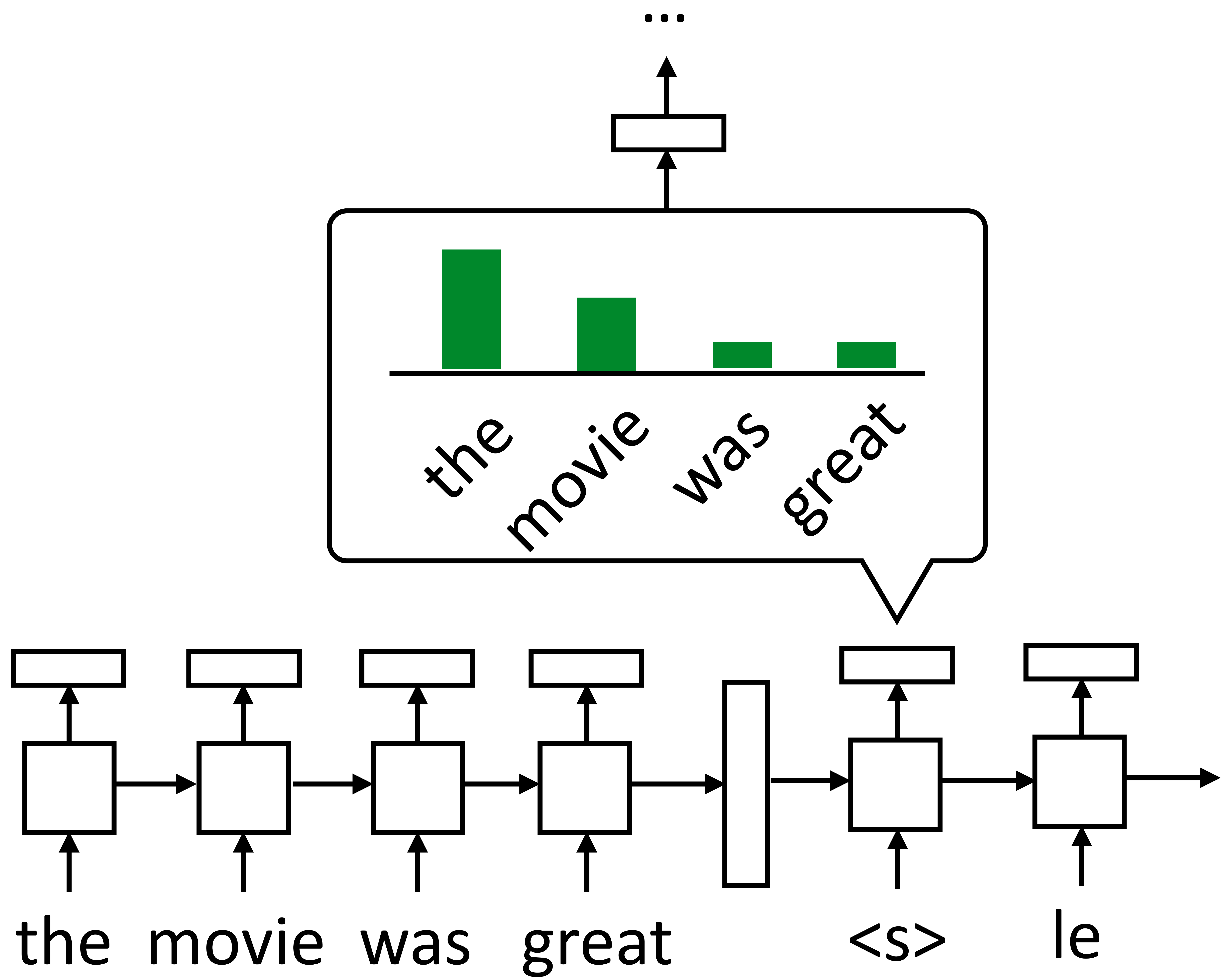

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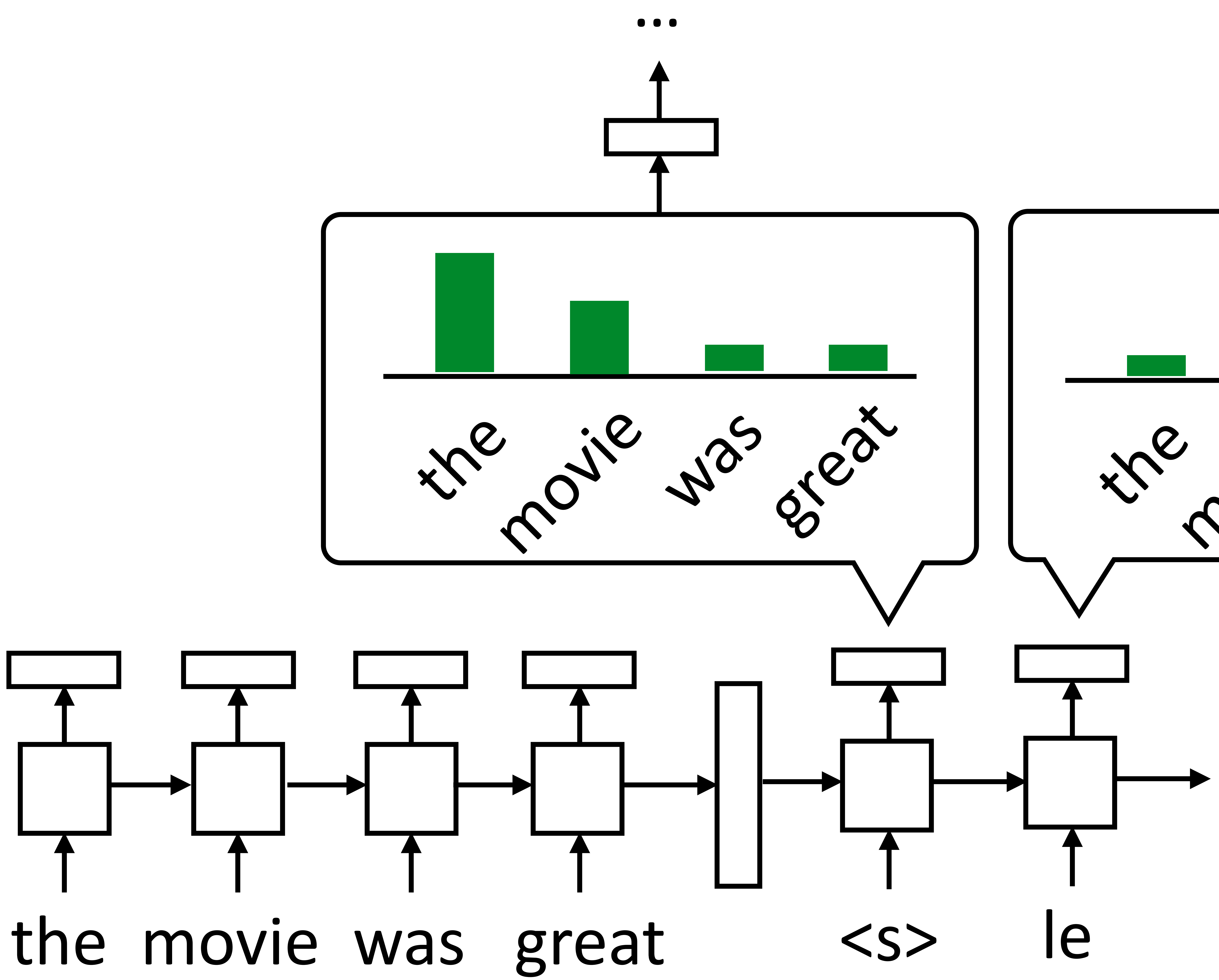
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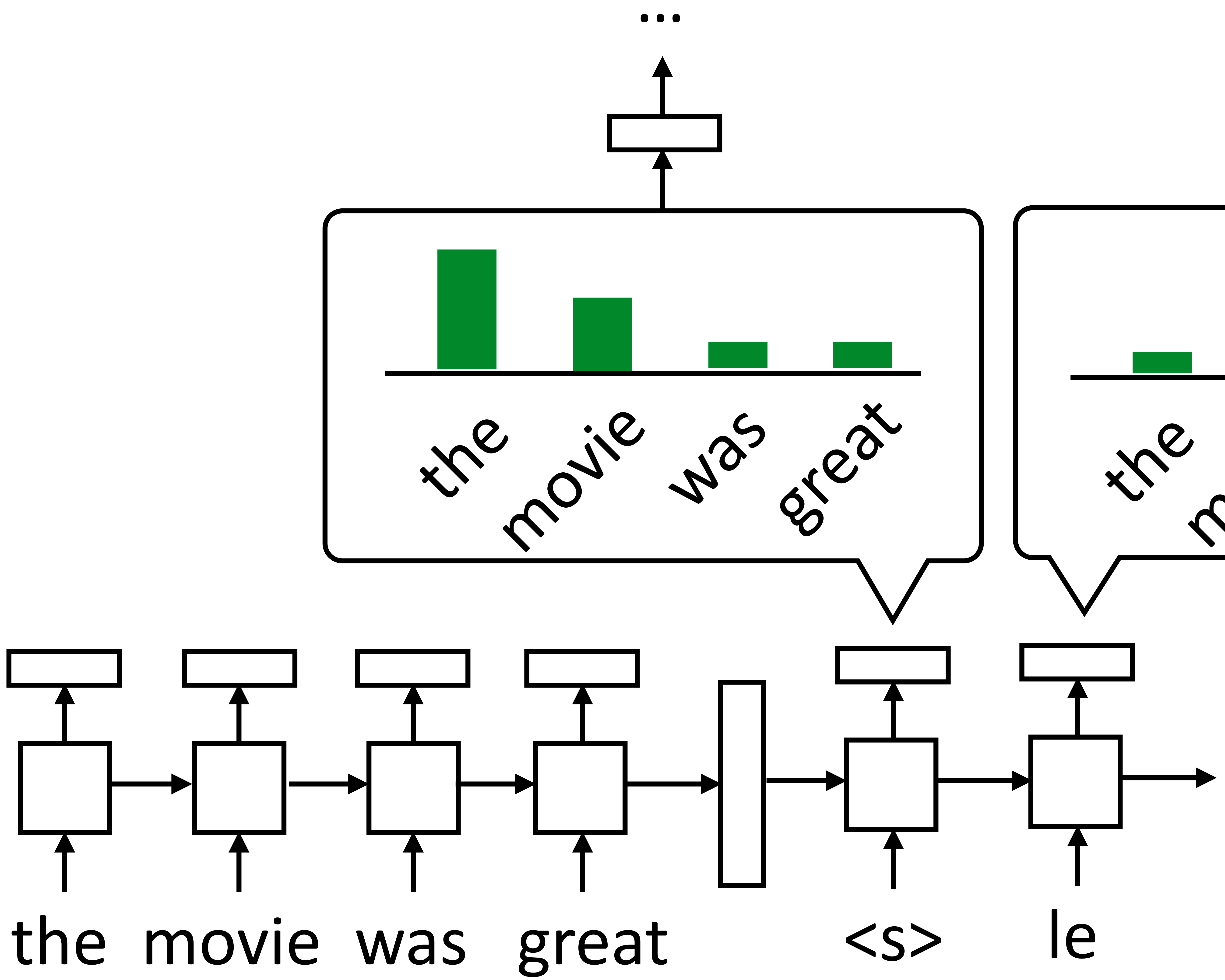
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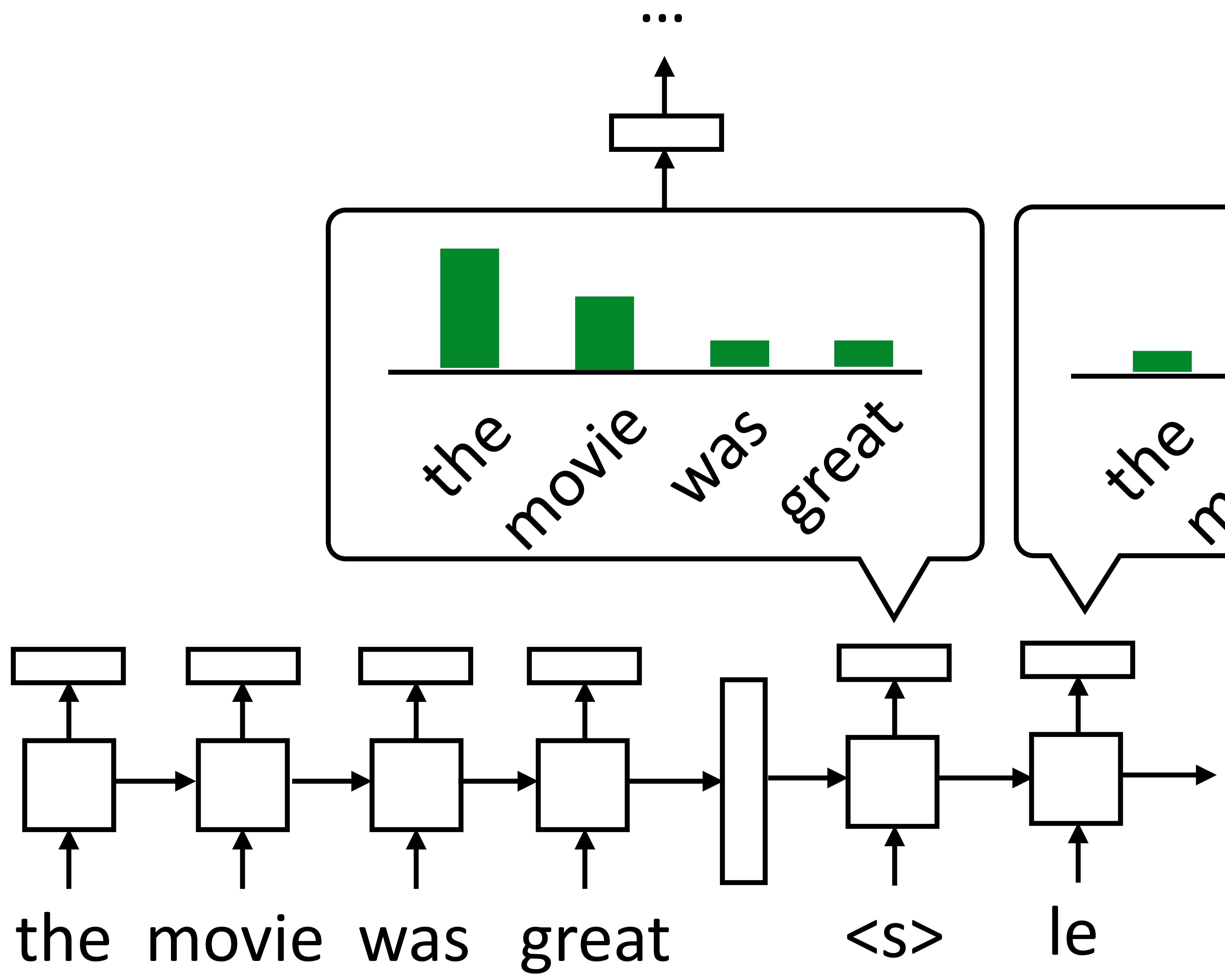

- At each decoder state, compute a distribution over source inputs based on current decoder state

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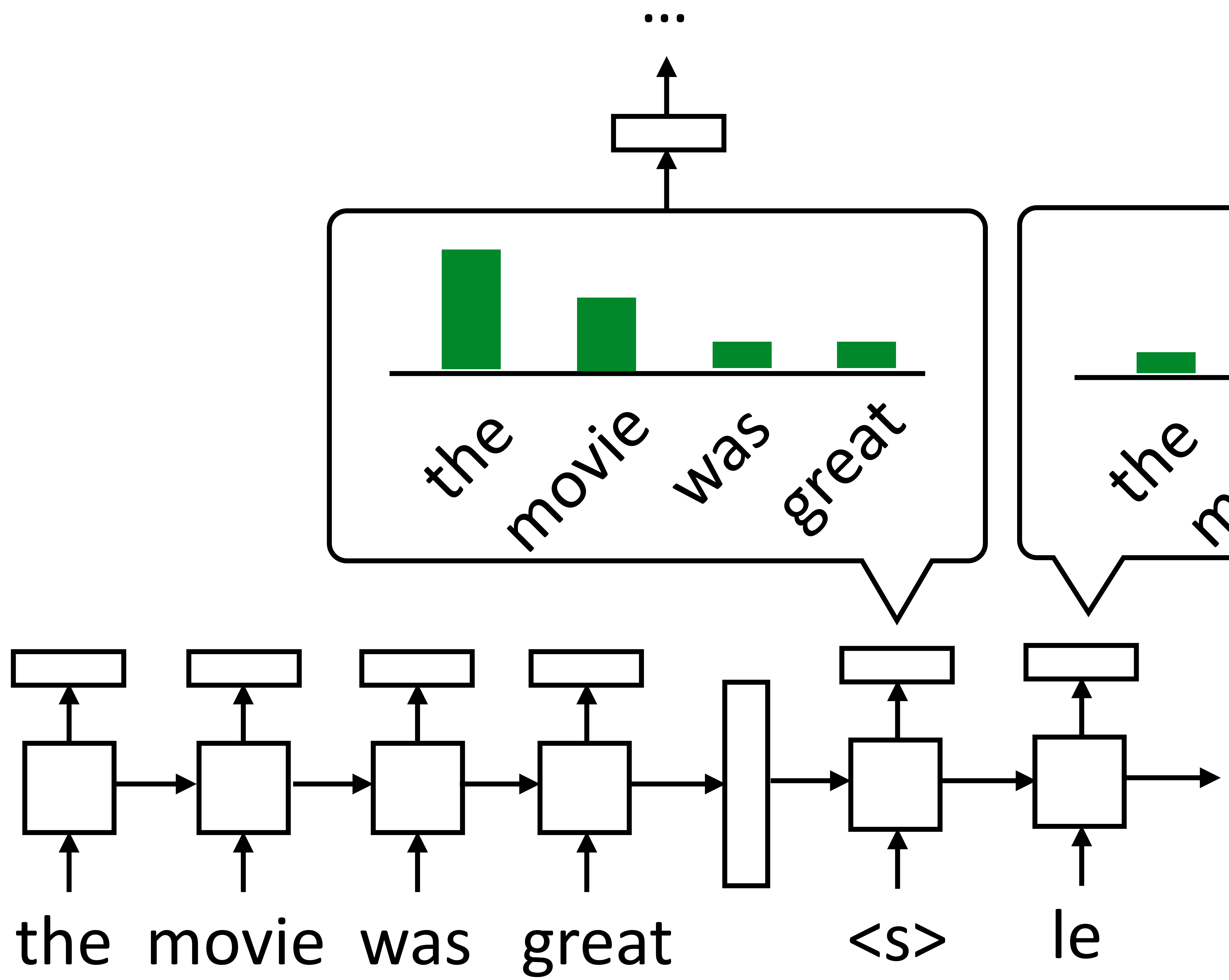
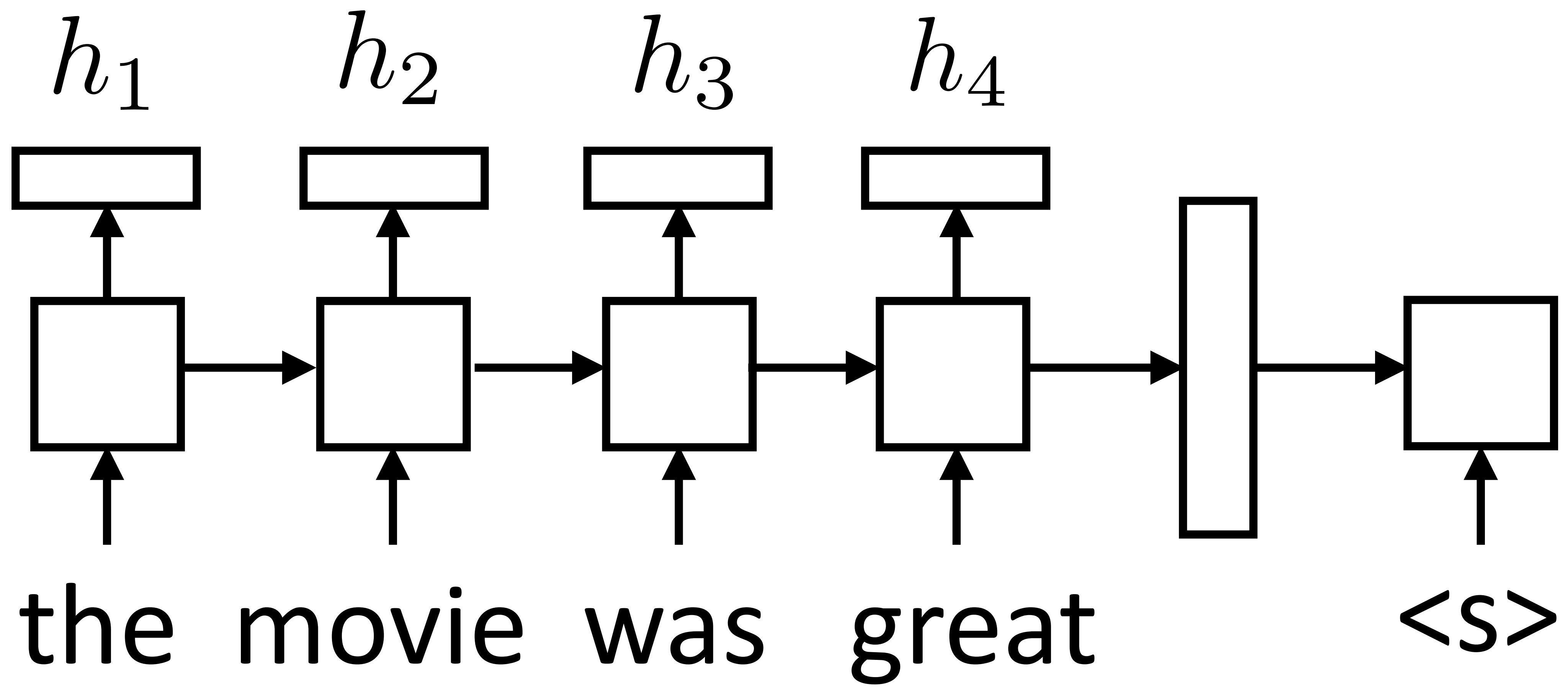


- At each decoder state, compute a distribution over source inputs based on current decoder state
- Use that in output layer

Attention

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



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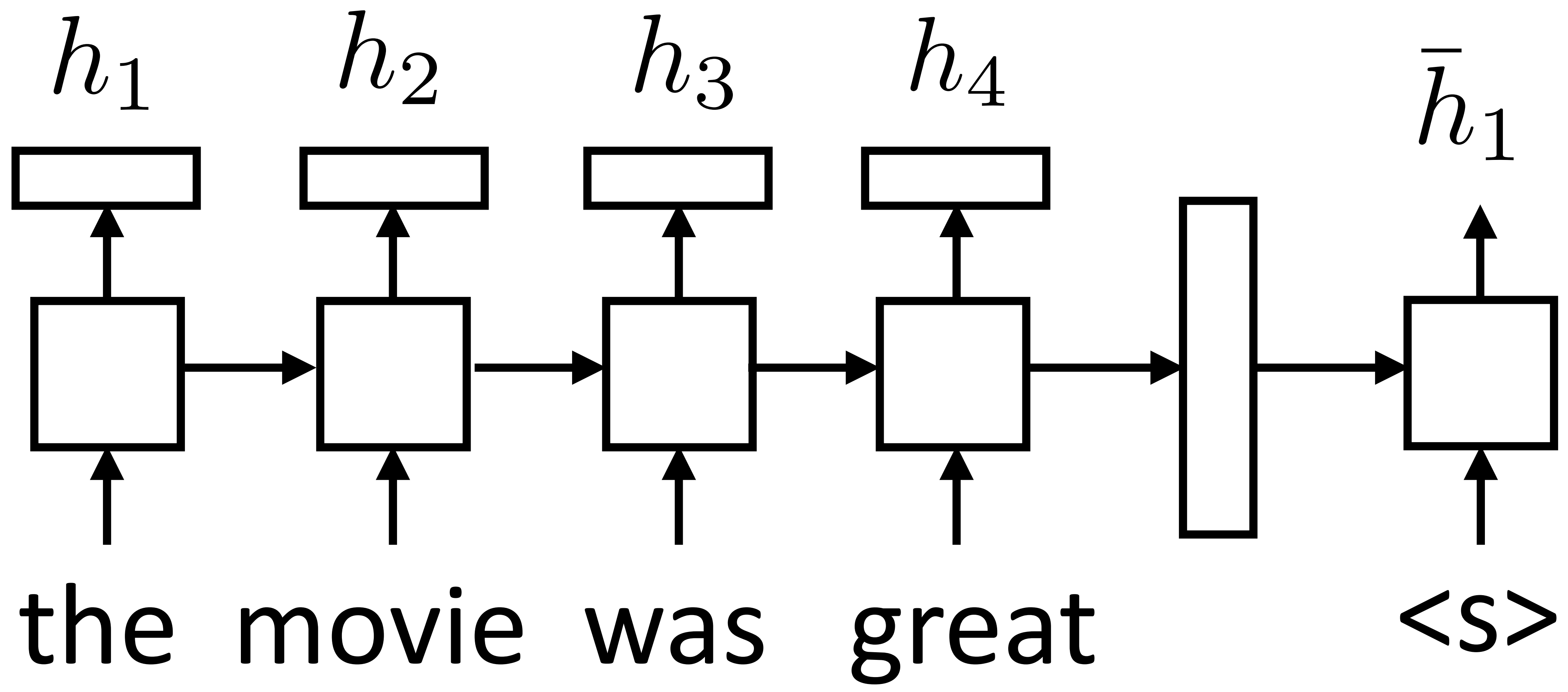

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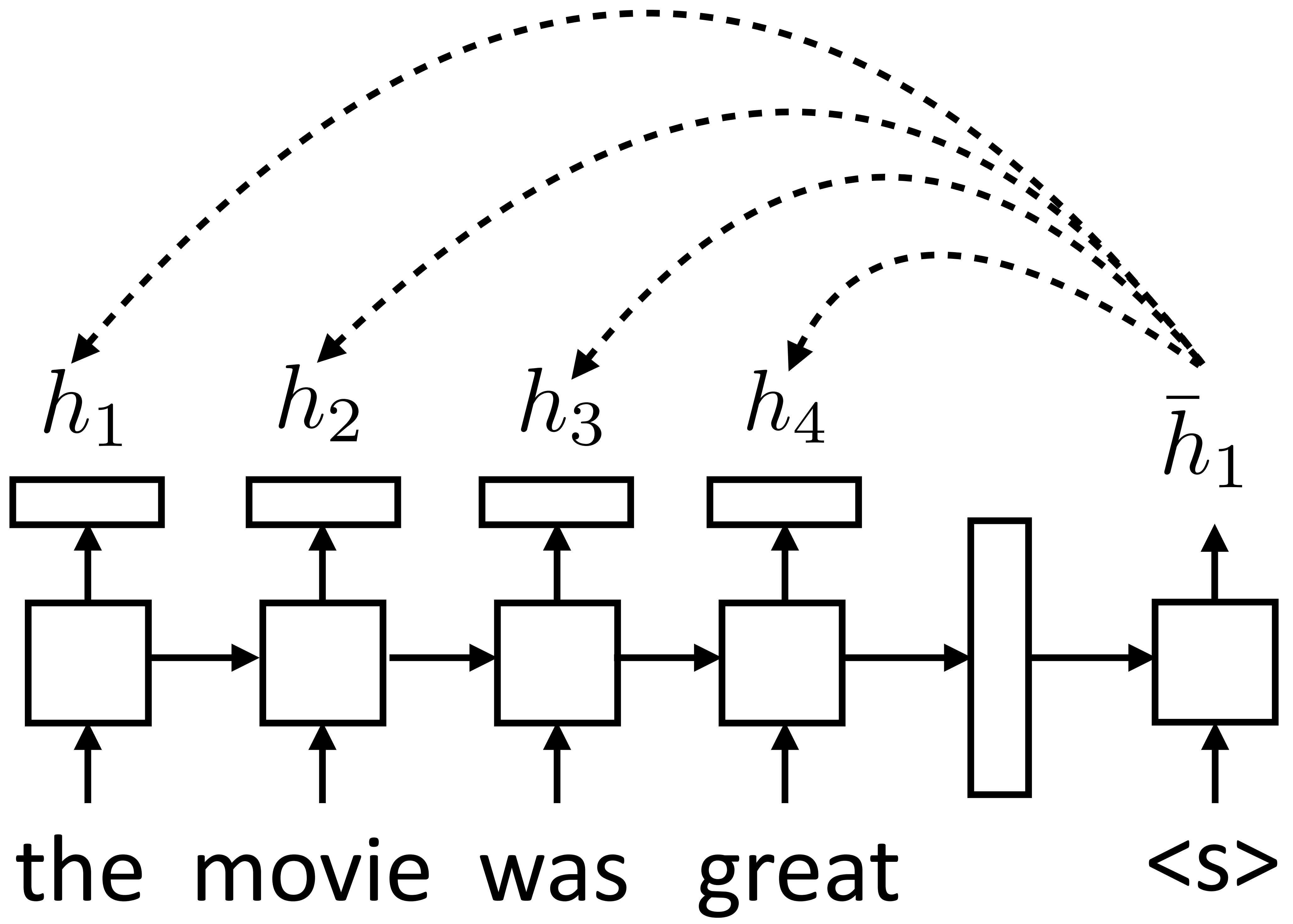

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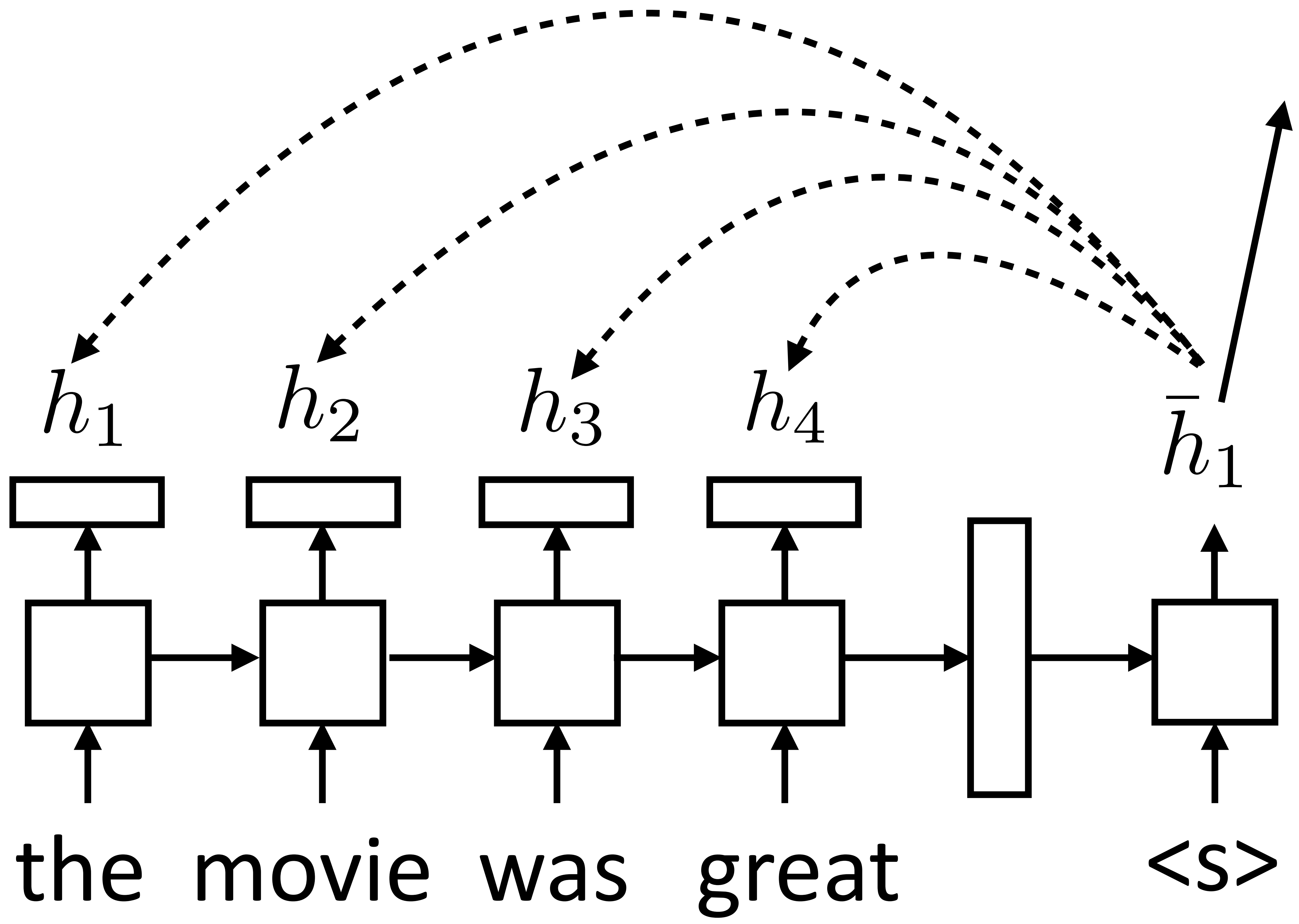

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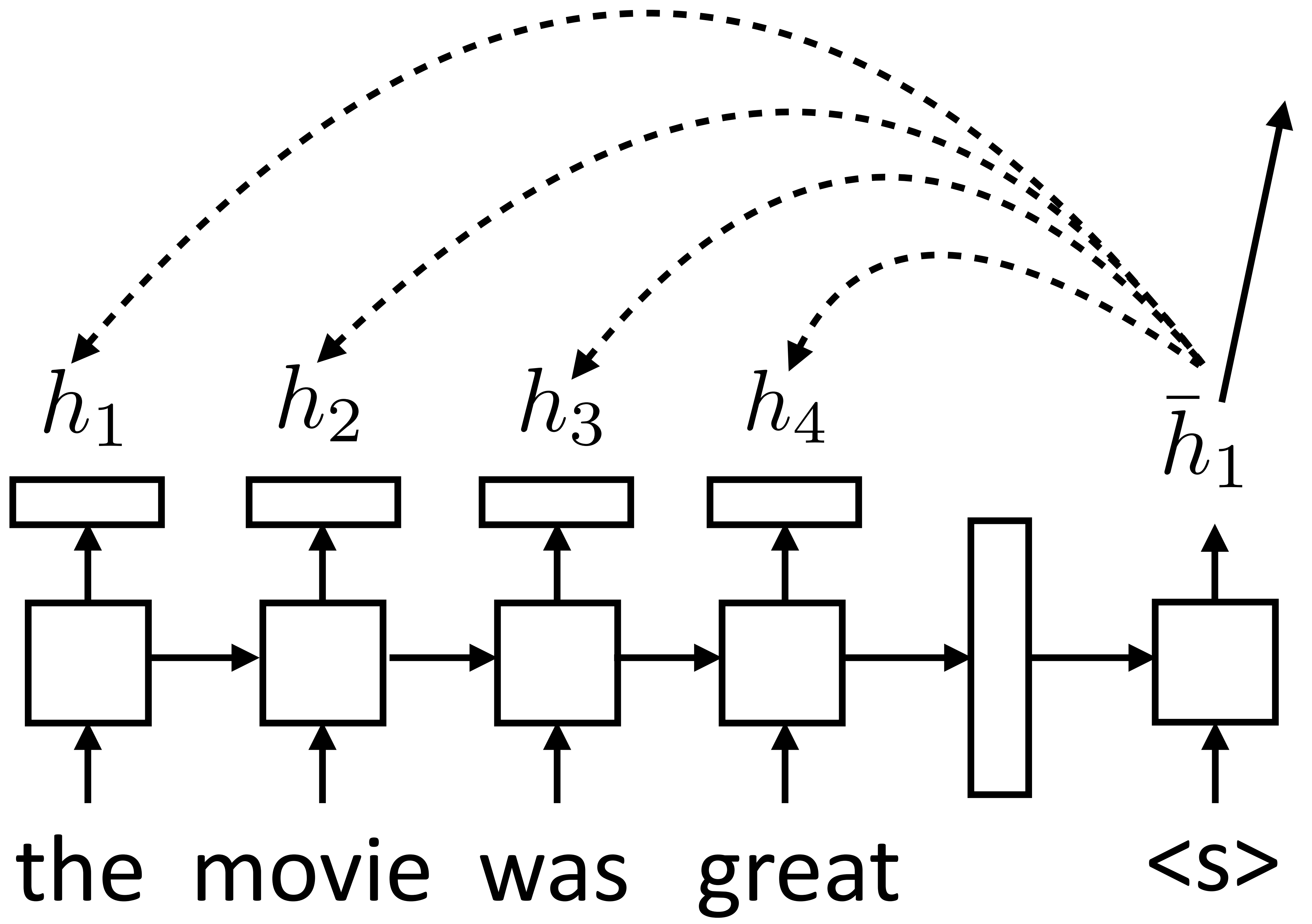

$$e_{ij} = f(\bar{h}_i, h_j)$$

- Unnormalized scalar weight

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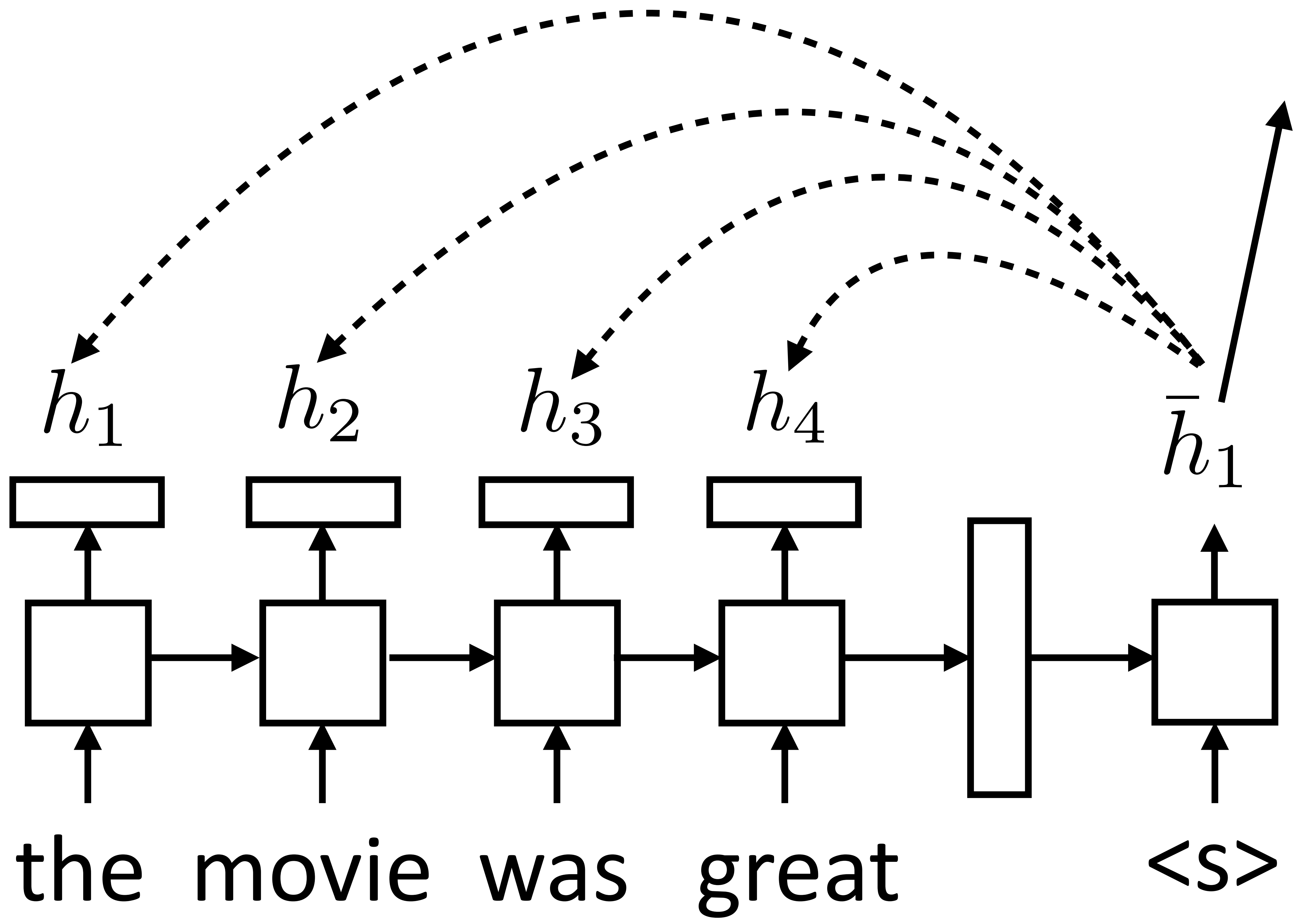

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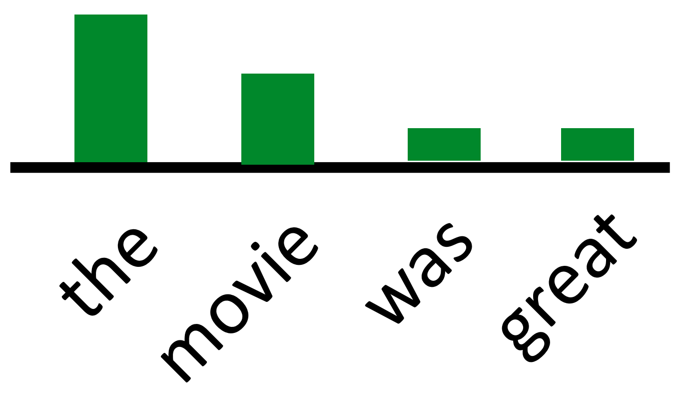

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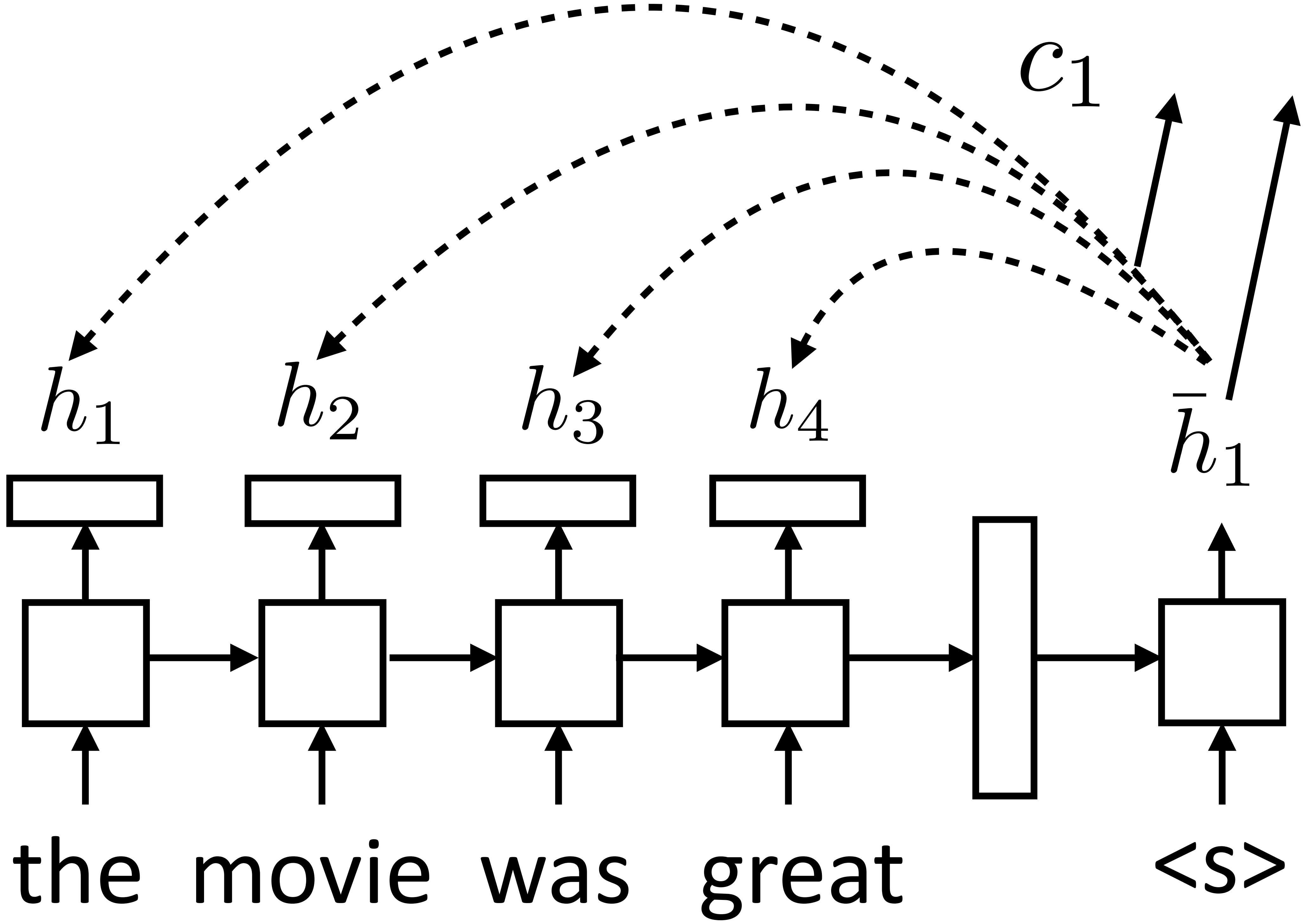

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- Weighted sum of input hidden states (vector)

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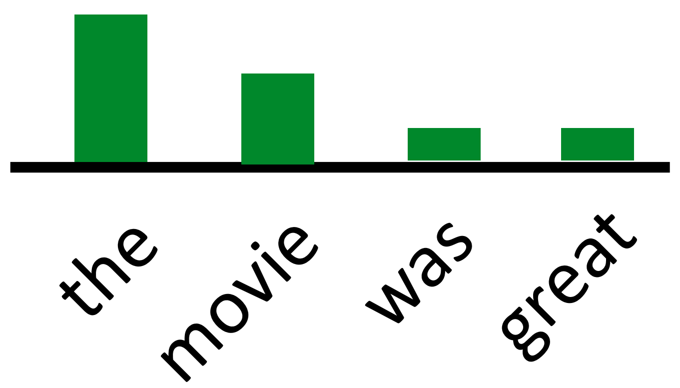

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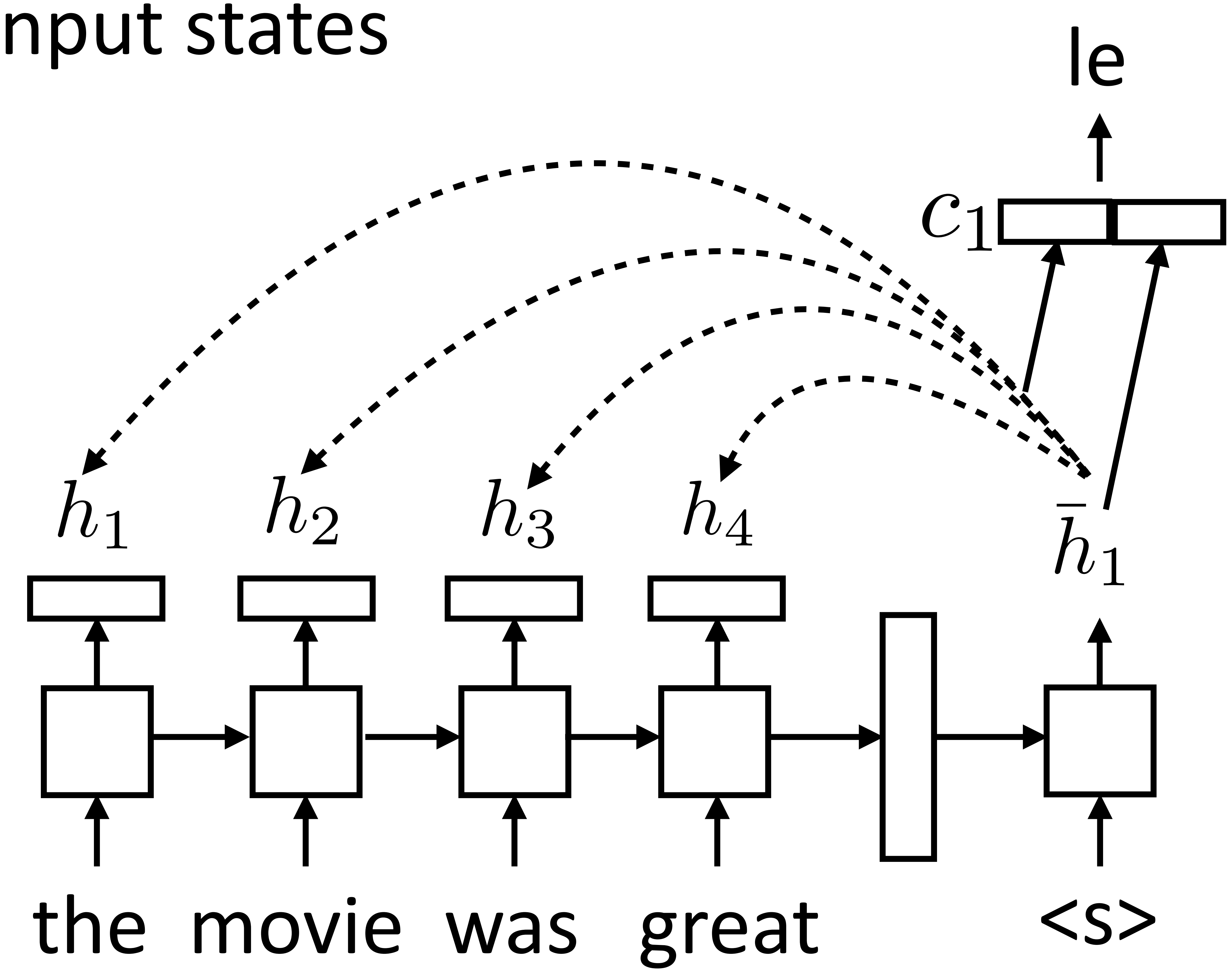

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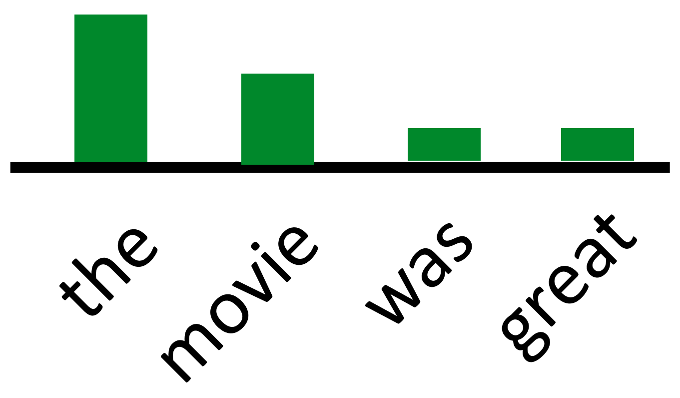

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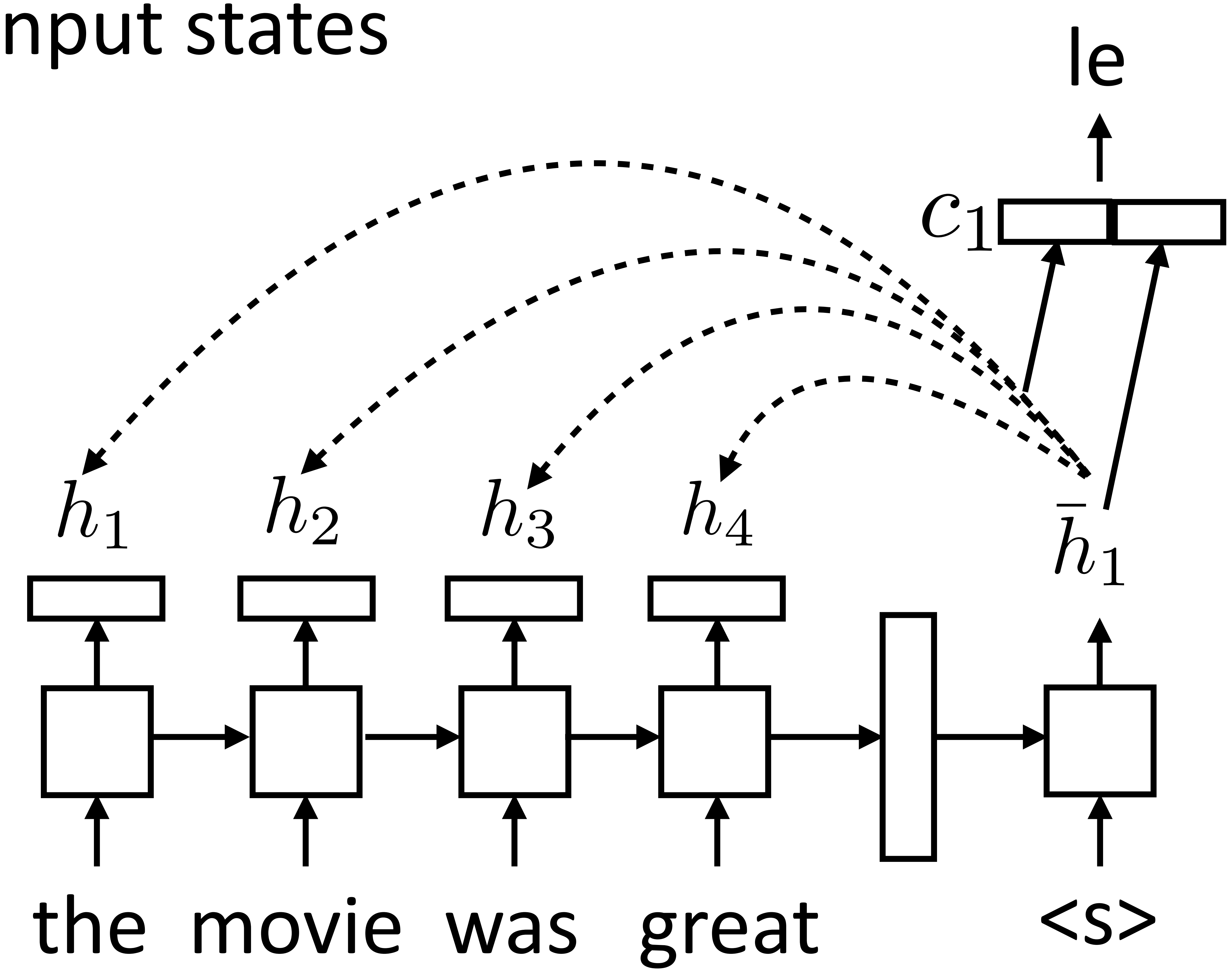

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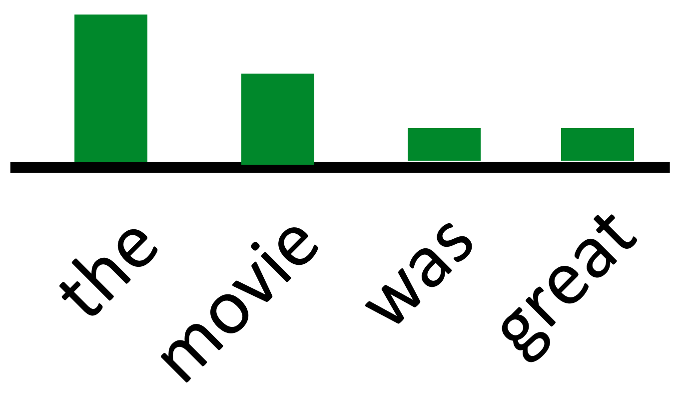

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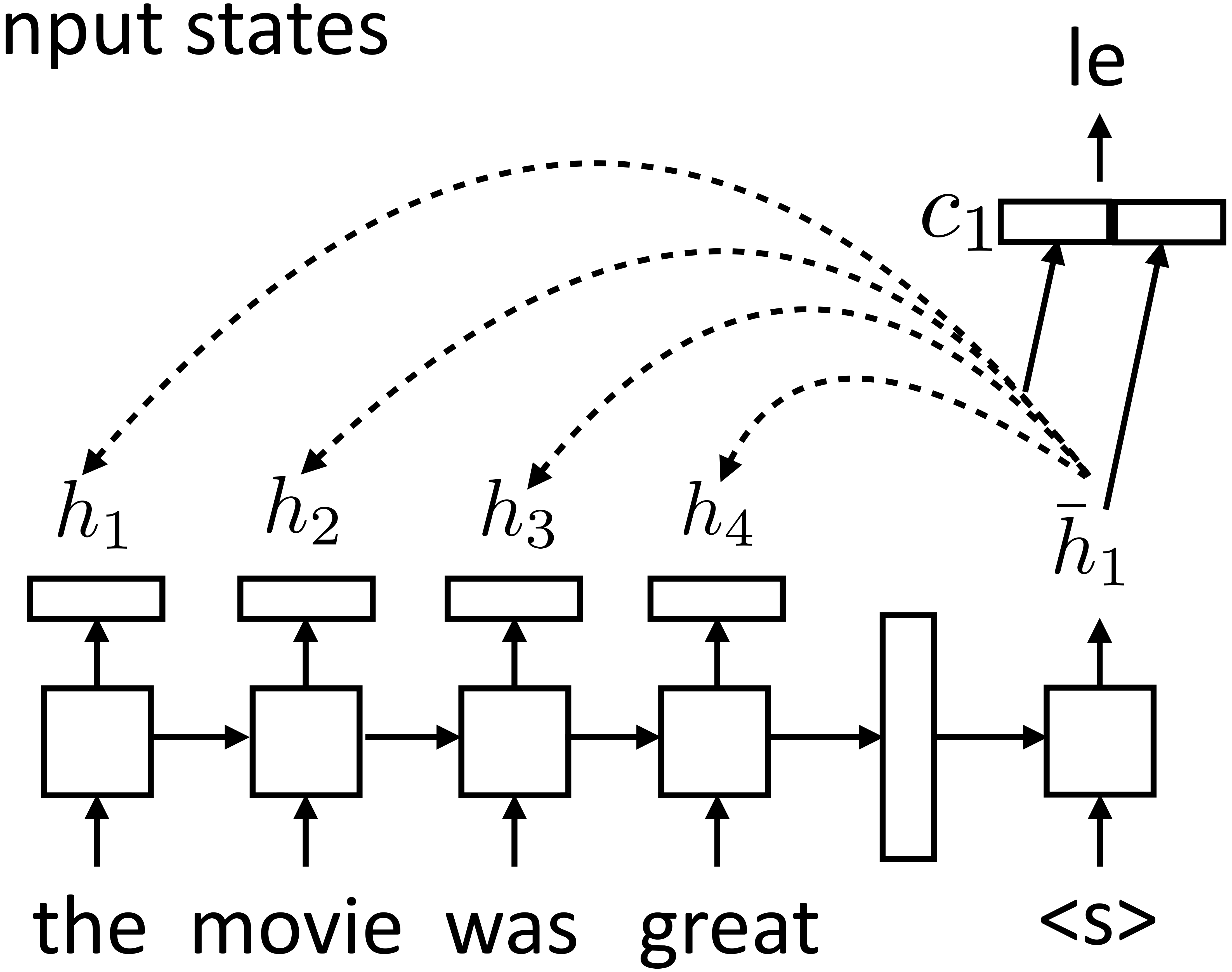

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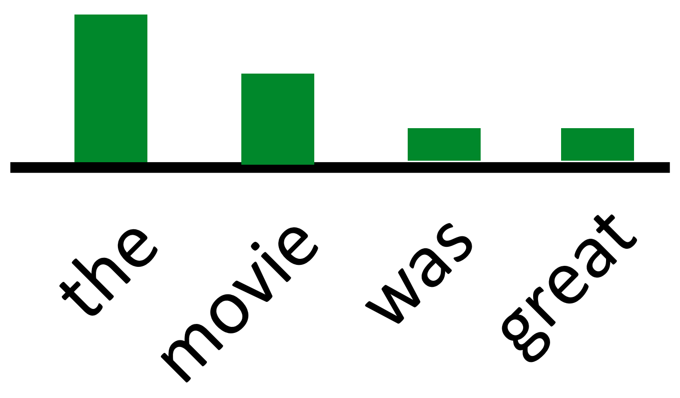

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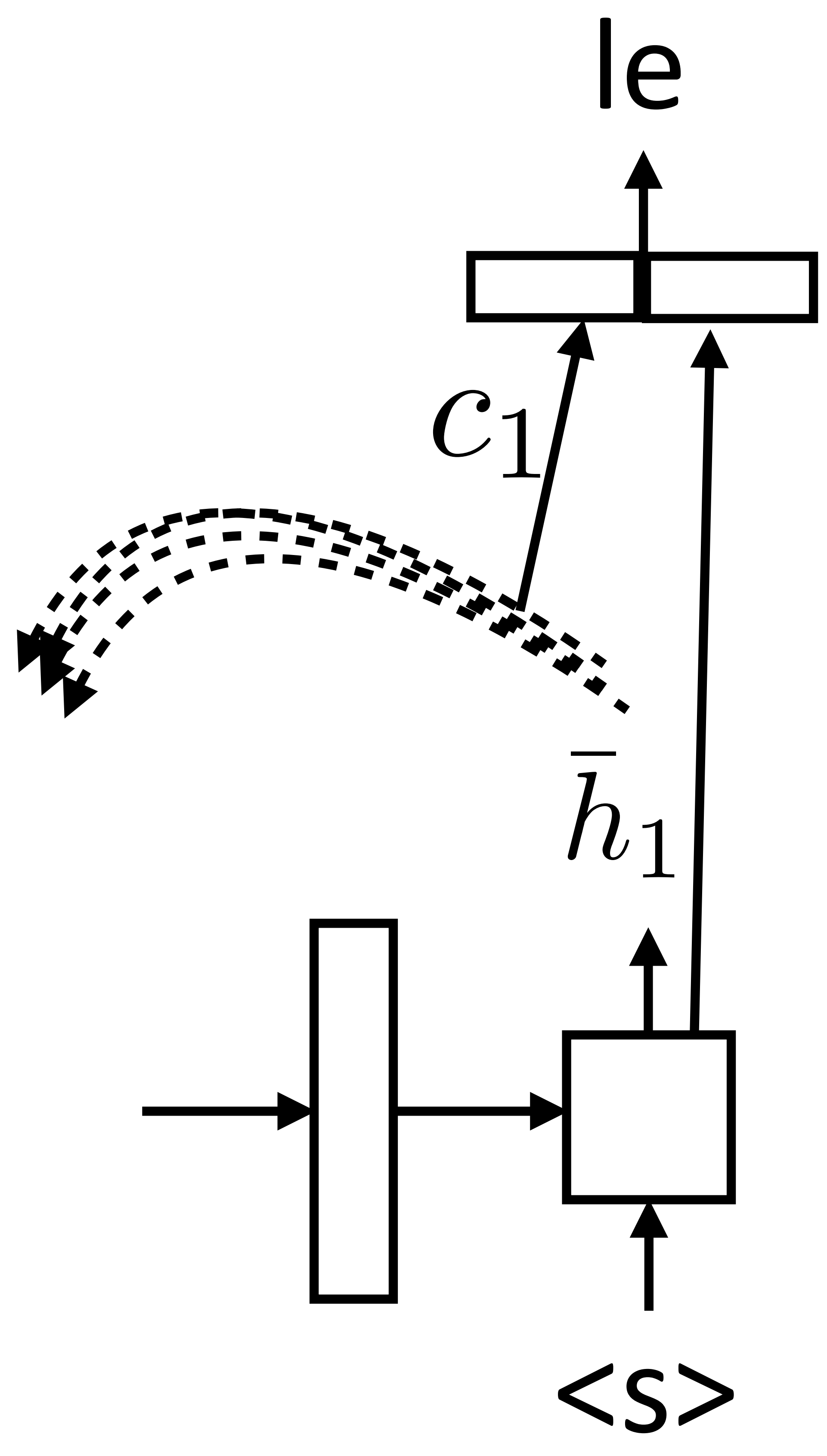

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Luong et al. (2015)

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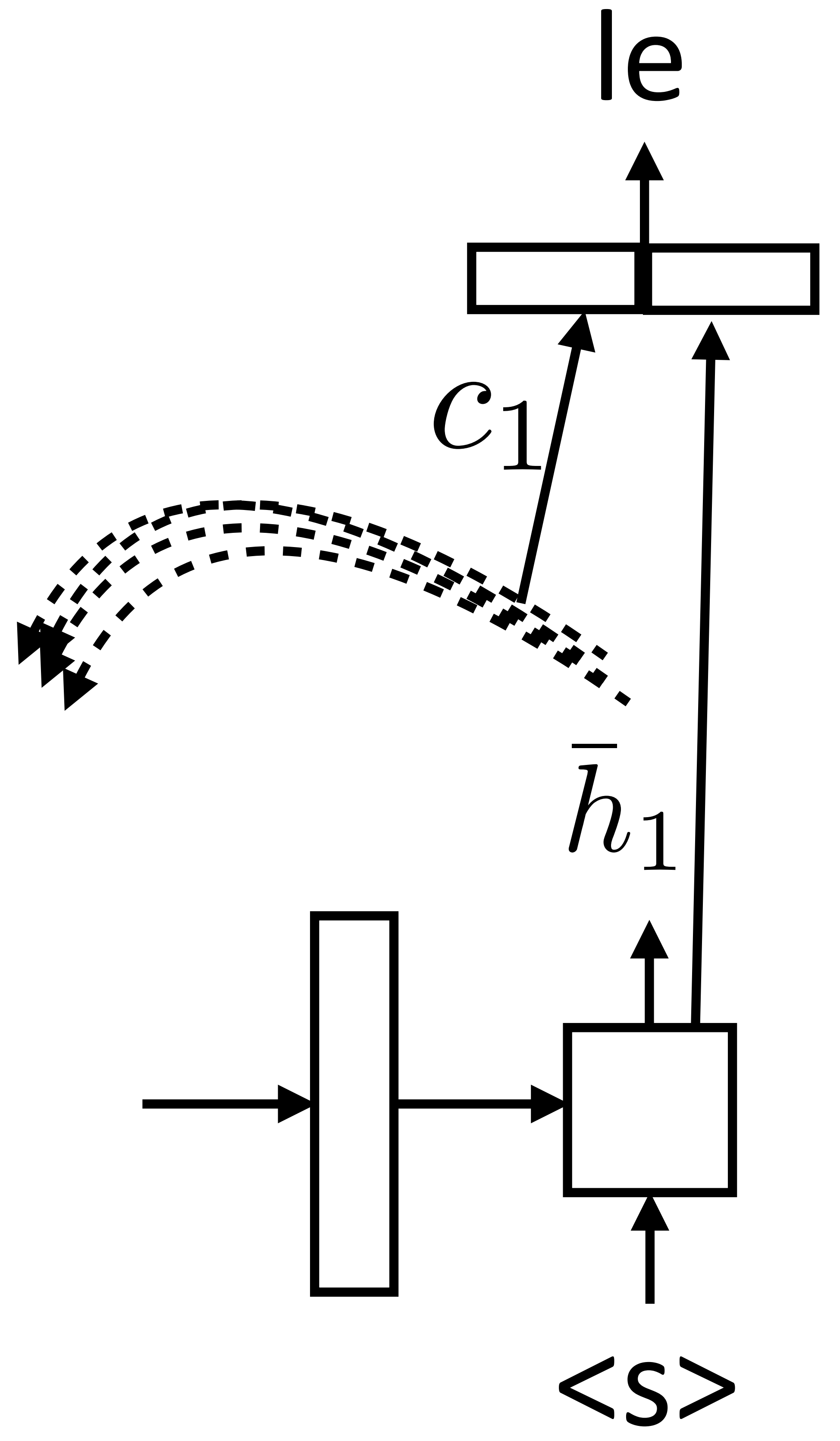

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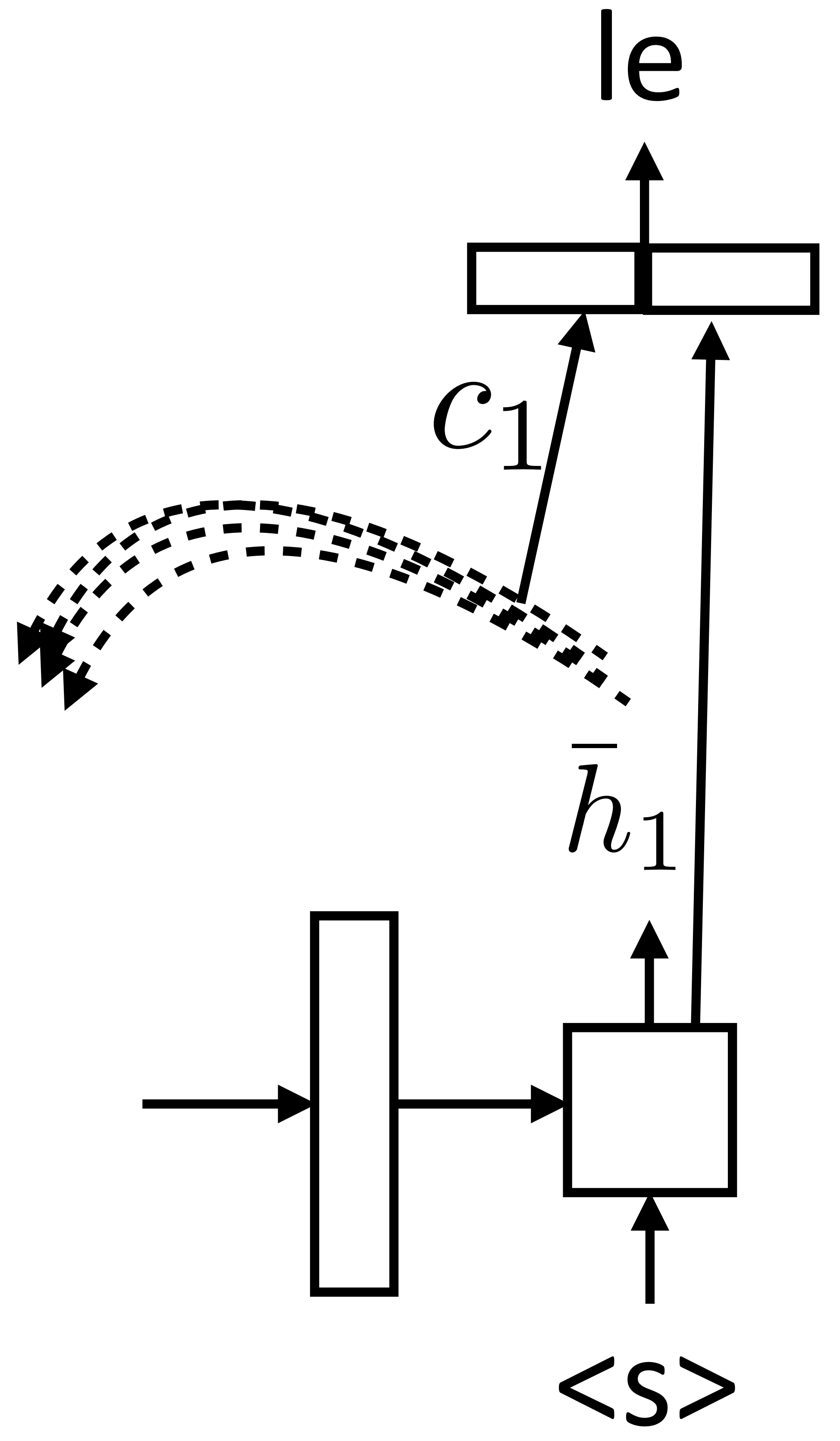

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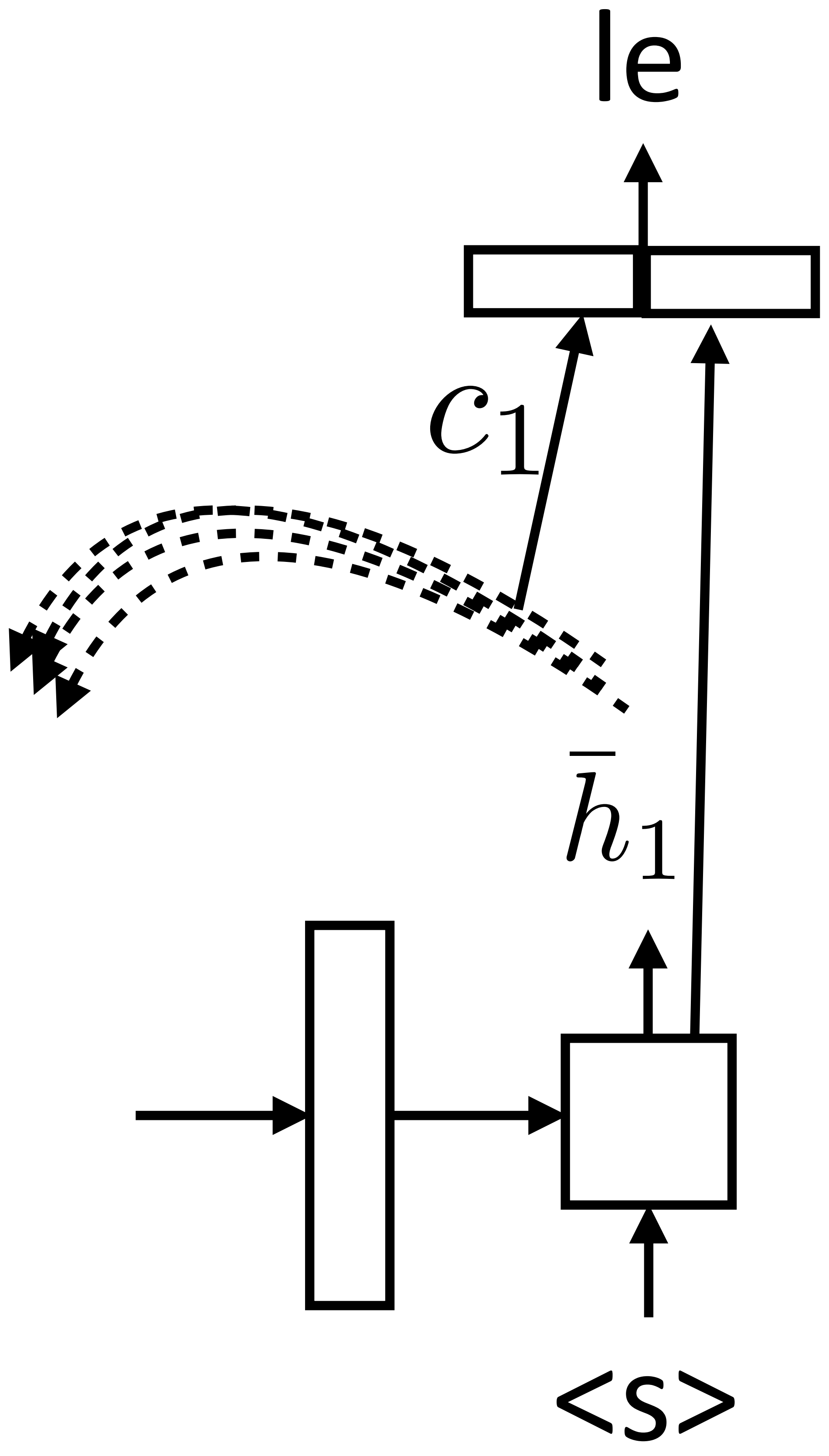

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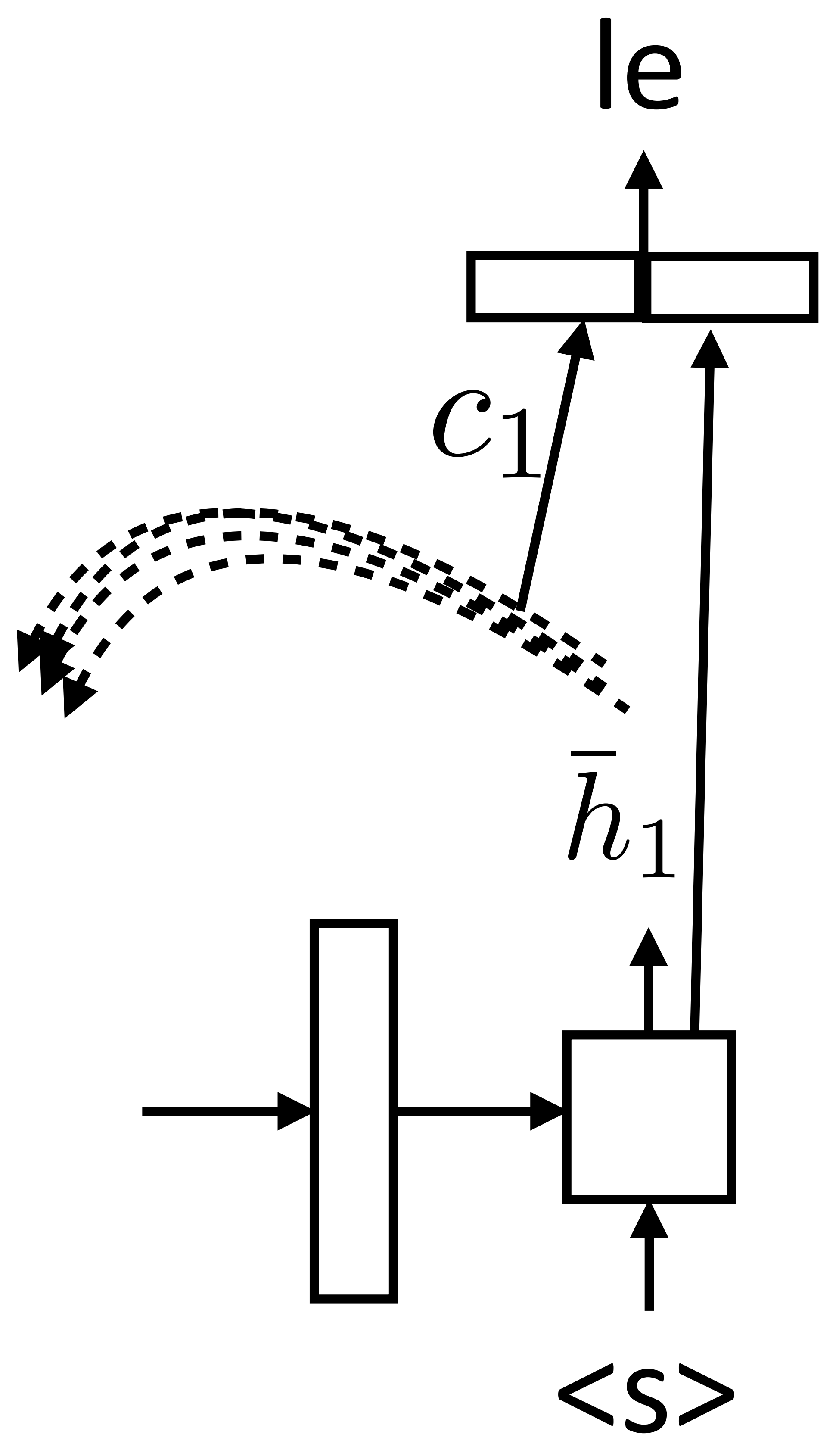

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- Note that this all uses outputs of hidden layers

Luong et al. (2015)

Copying Input/Pointers

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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

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

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

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from attention

from RNN hidden state

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

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

Copying

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

Copying

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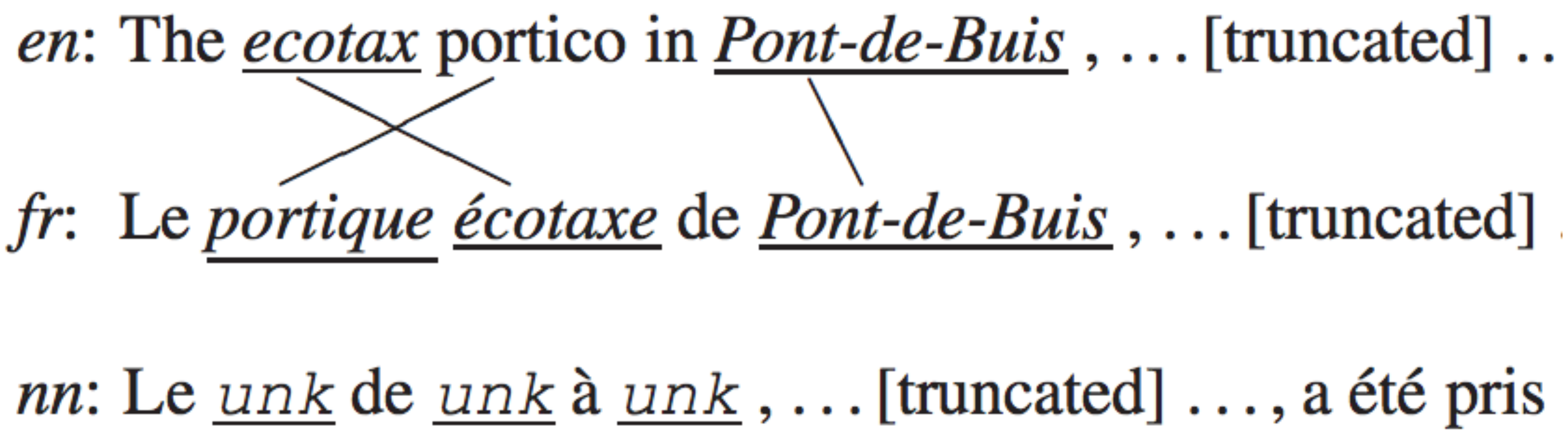
fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] .

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



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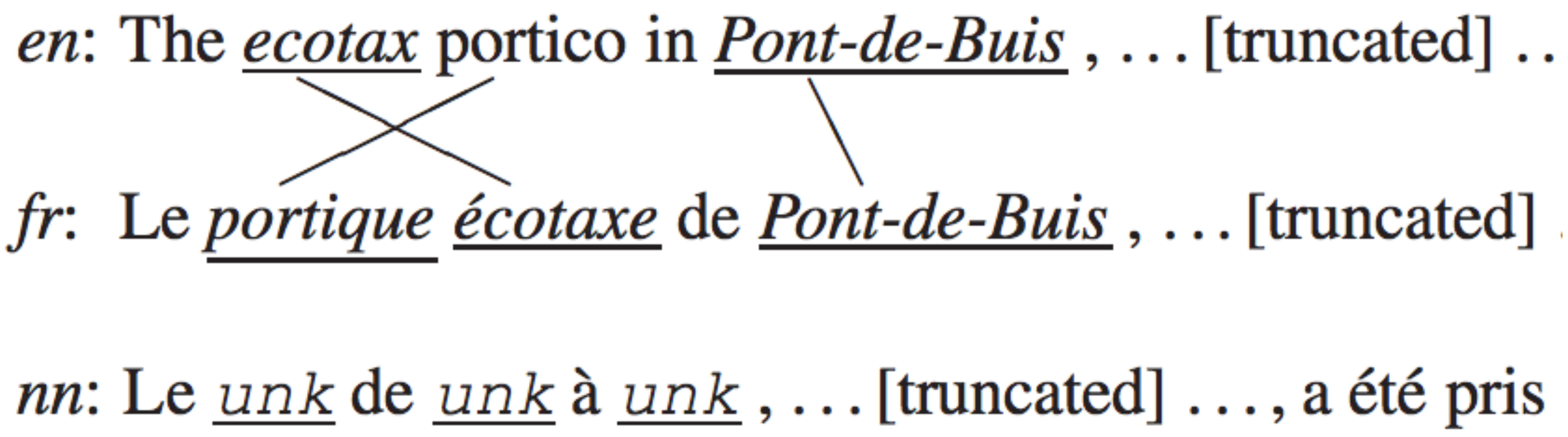

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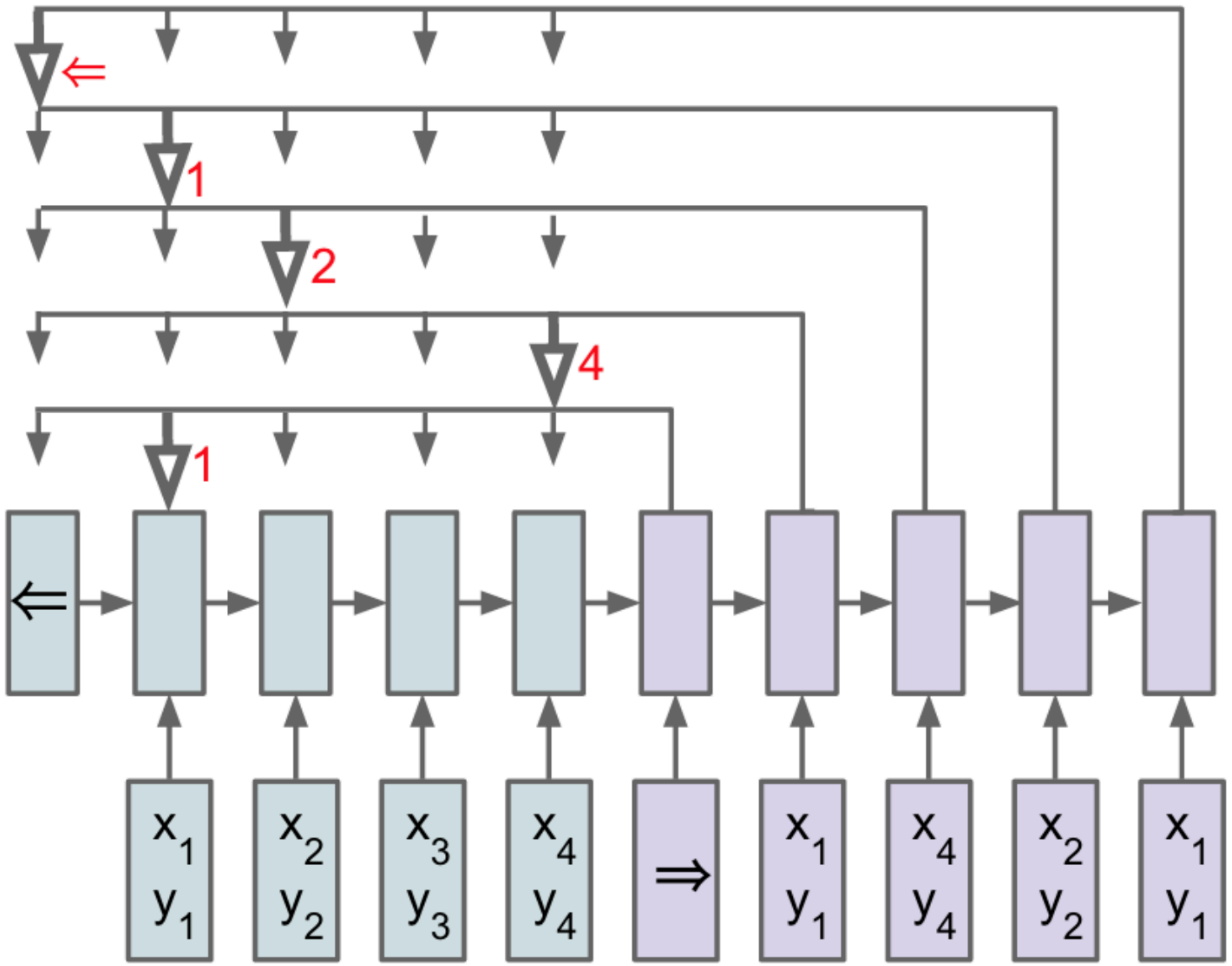
- Bilinear function of input representation + output hidden state

Pointer Networks



Vinyals et al. (2015)

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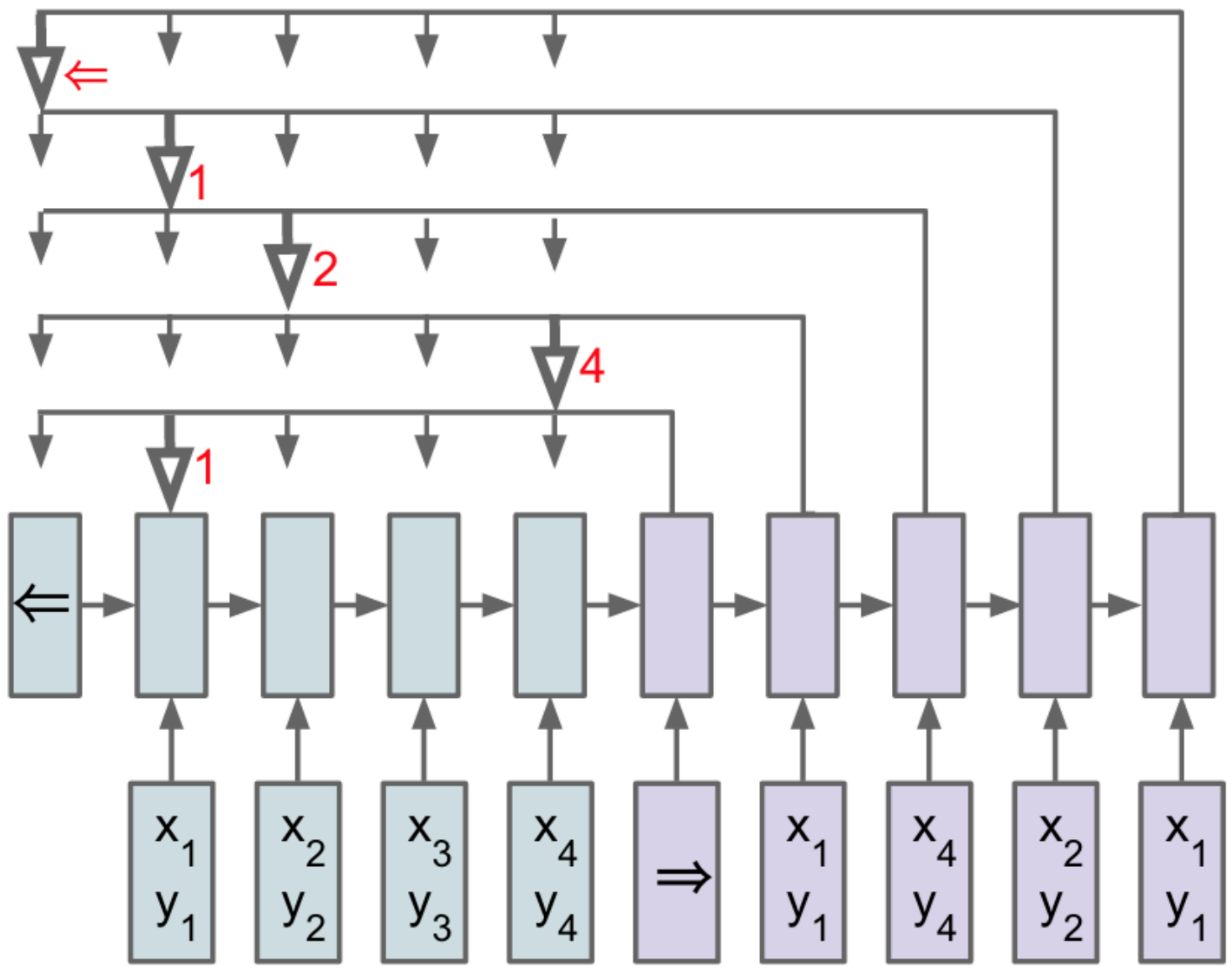

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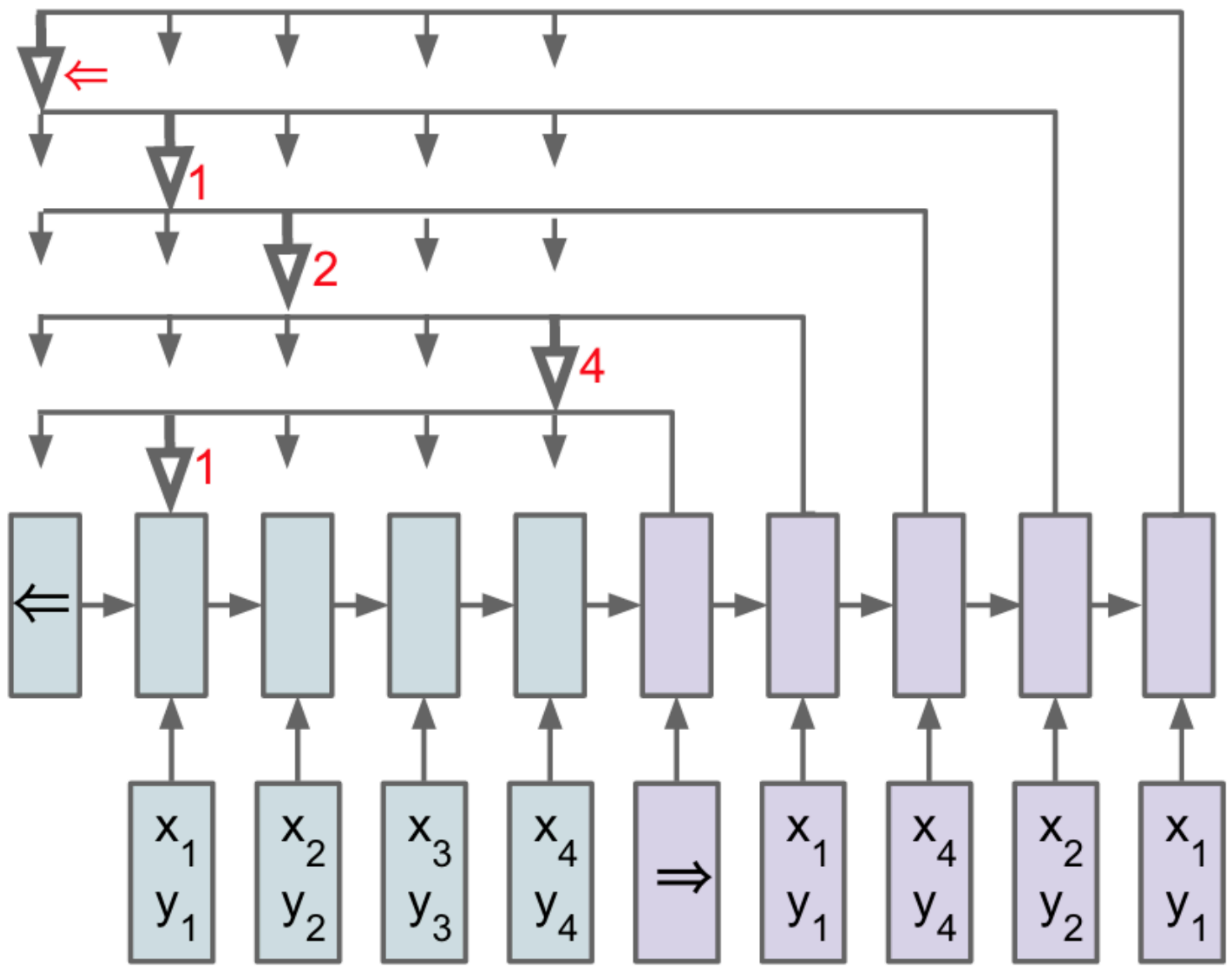

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Results

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

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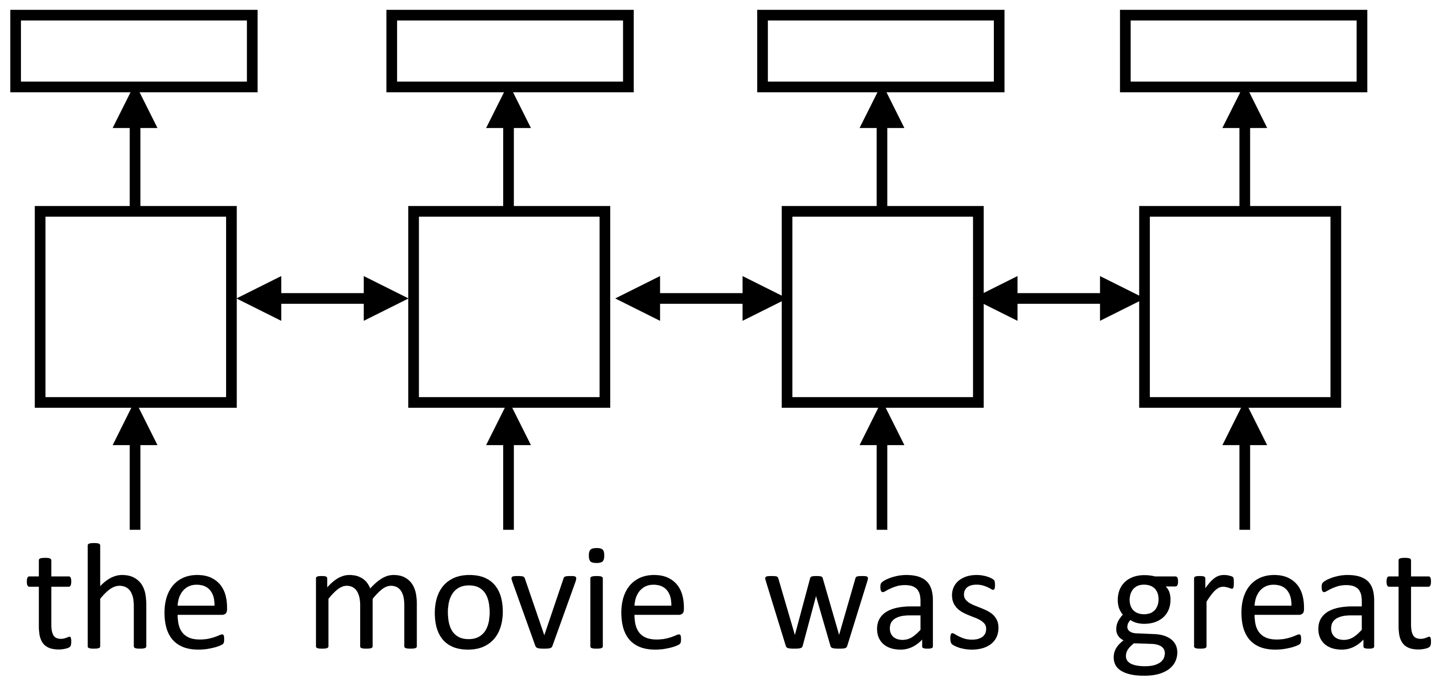
- In many settings, attention can roughly do the same things as copying

Jia and Liang (2016)

Transformers

Self-Attention

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



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Self-Attention

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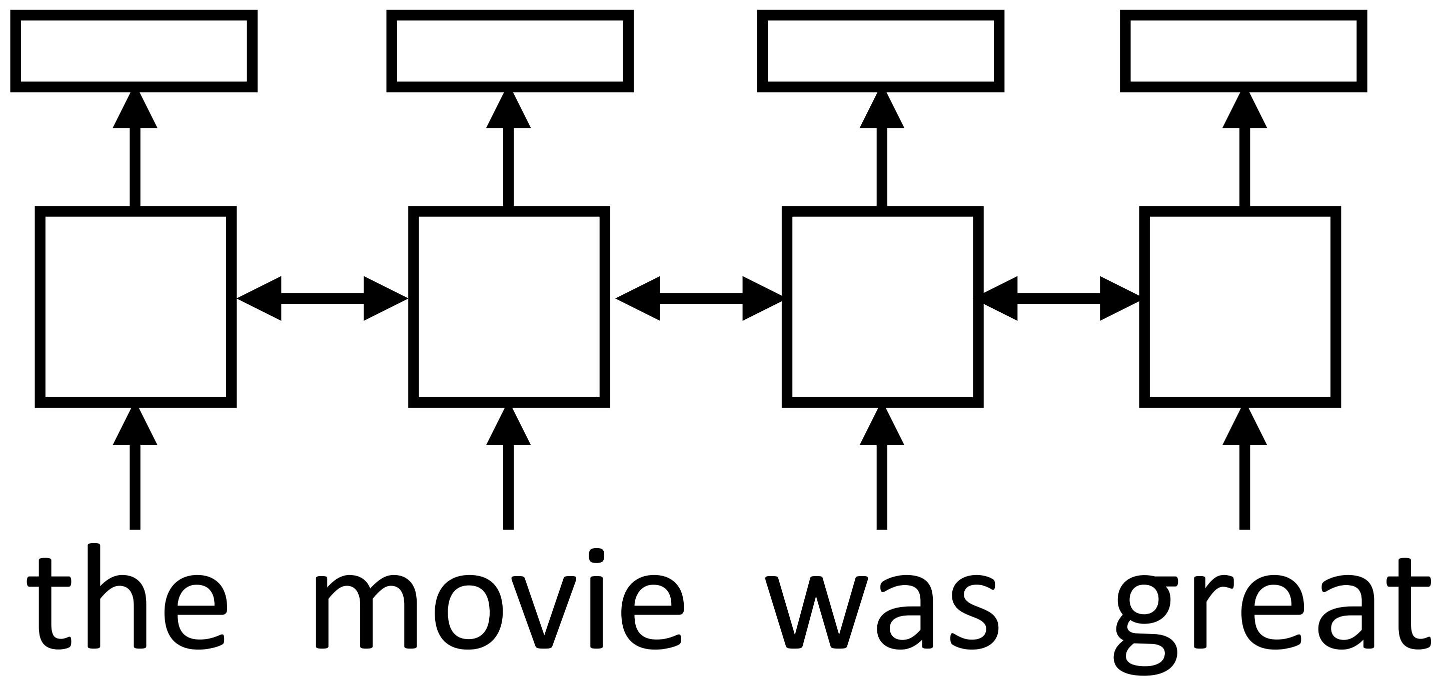

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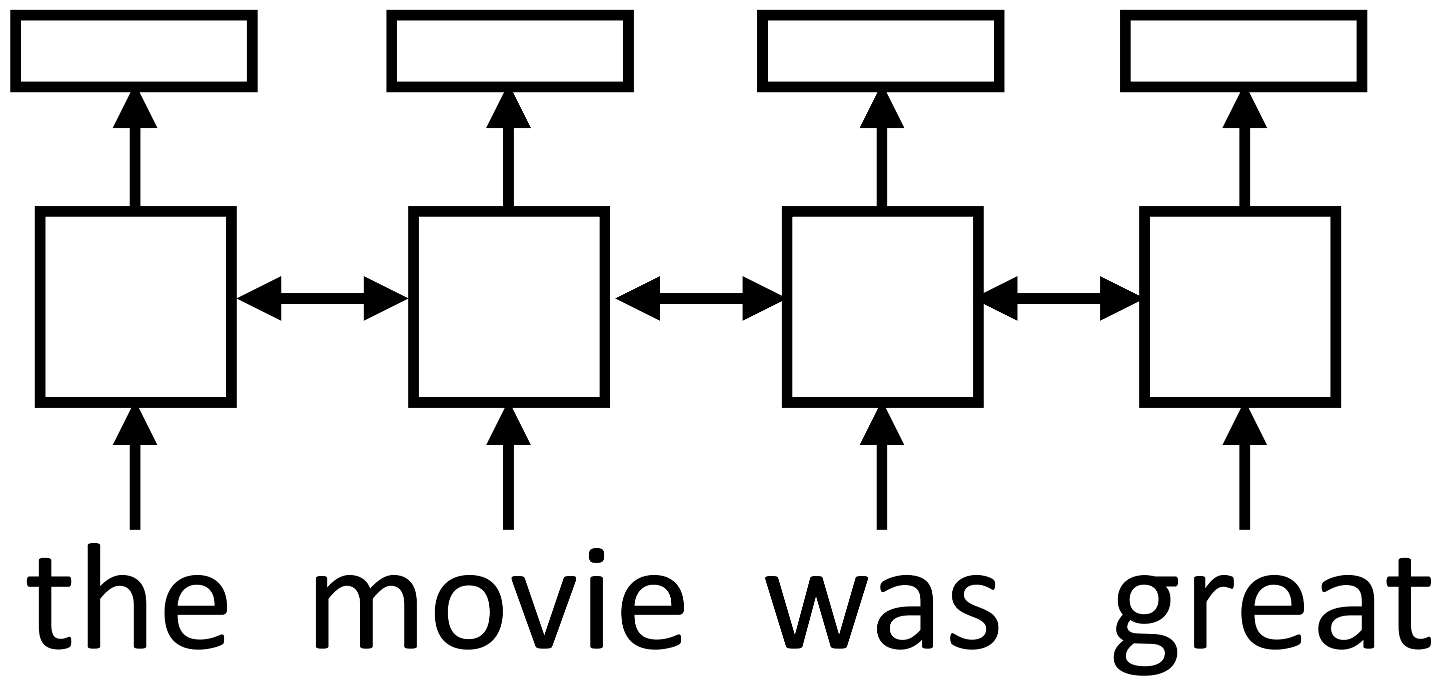
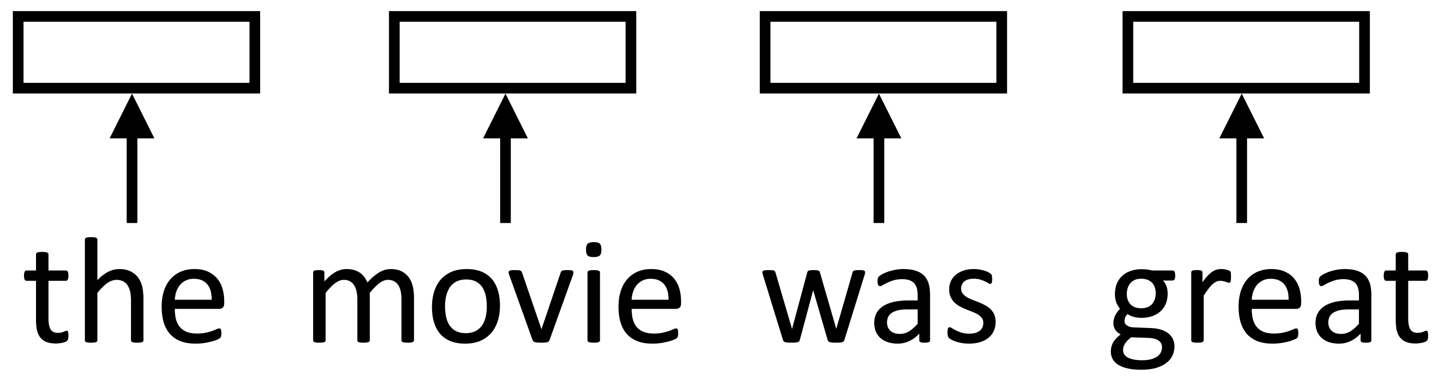


- Attention can give us a third way to do this

Vaswani et al. (2017)

Self-Attention

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



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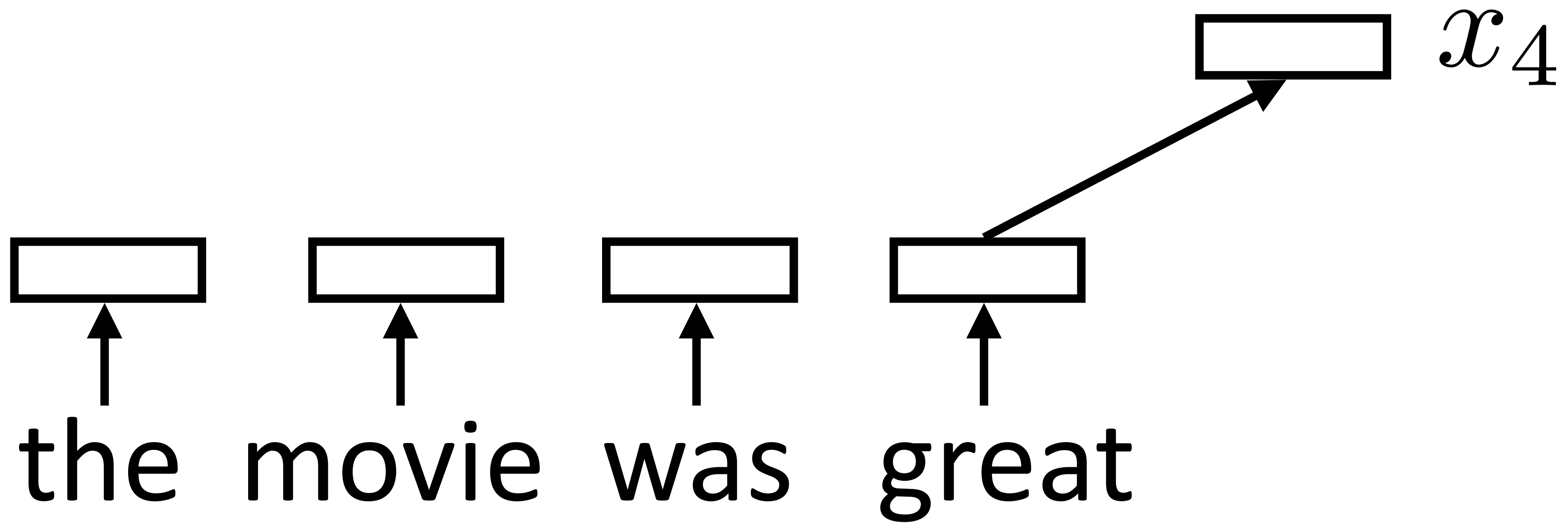

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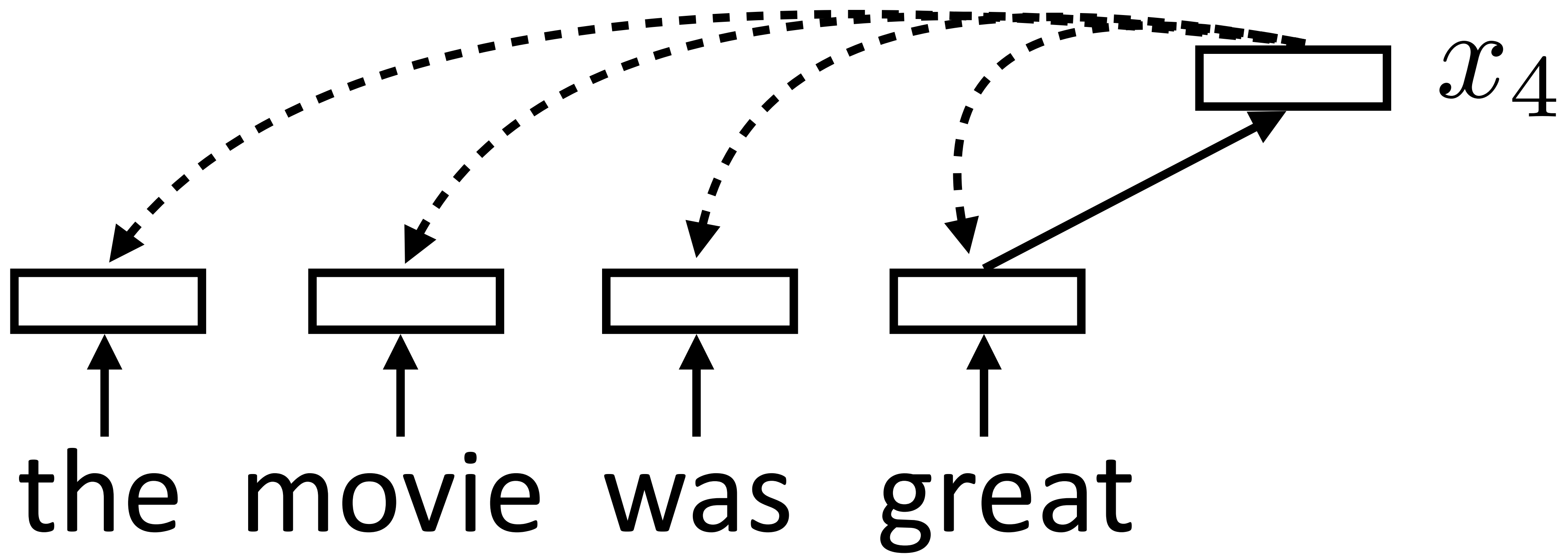

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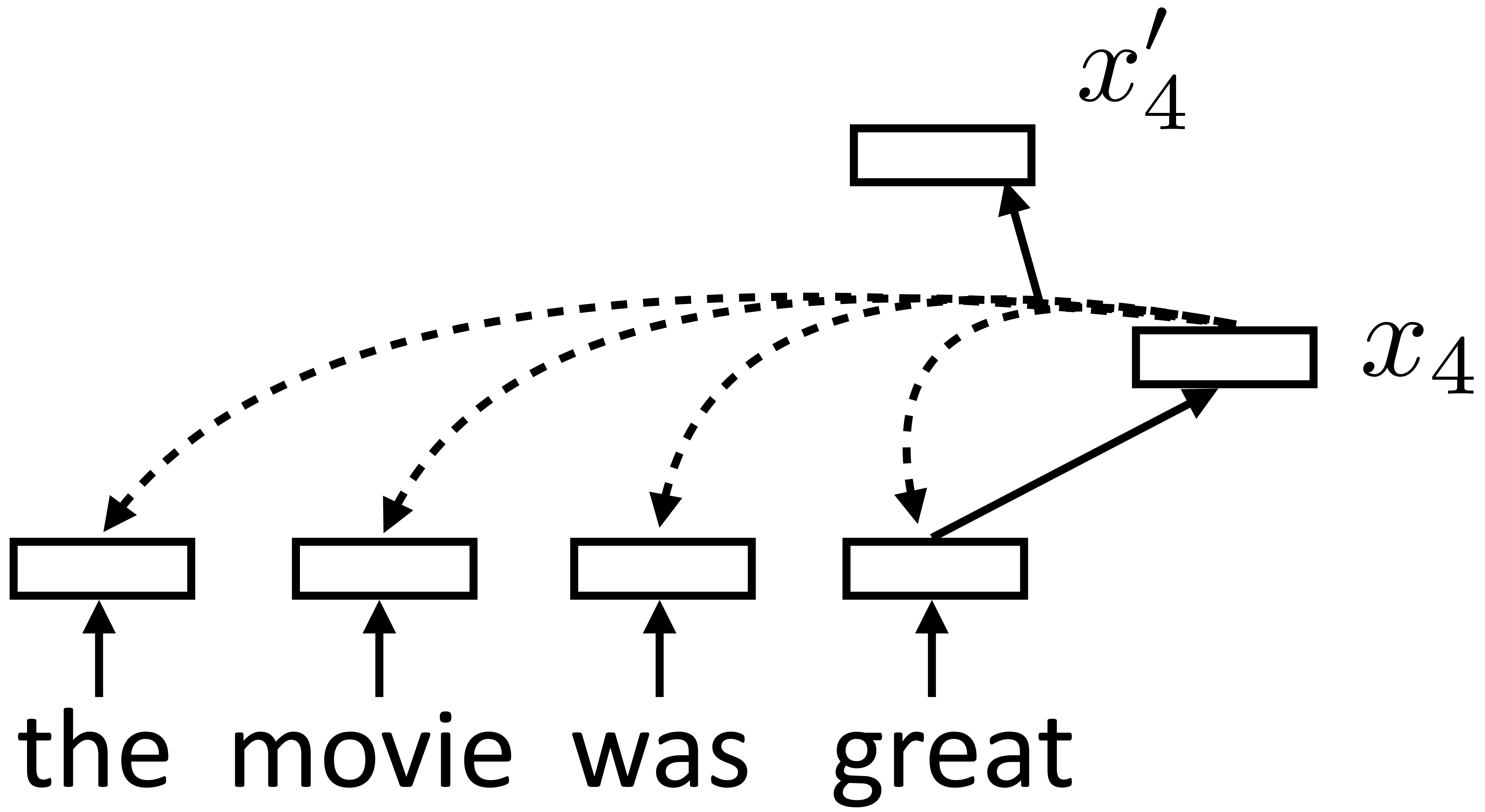

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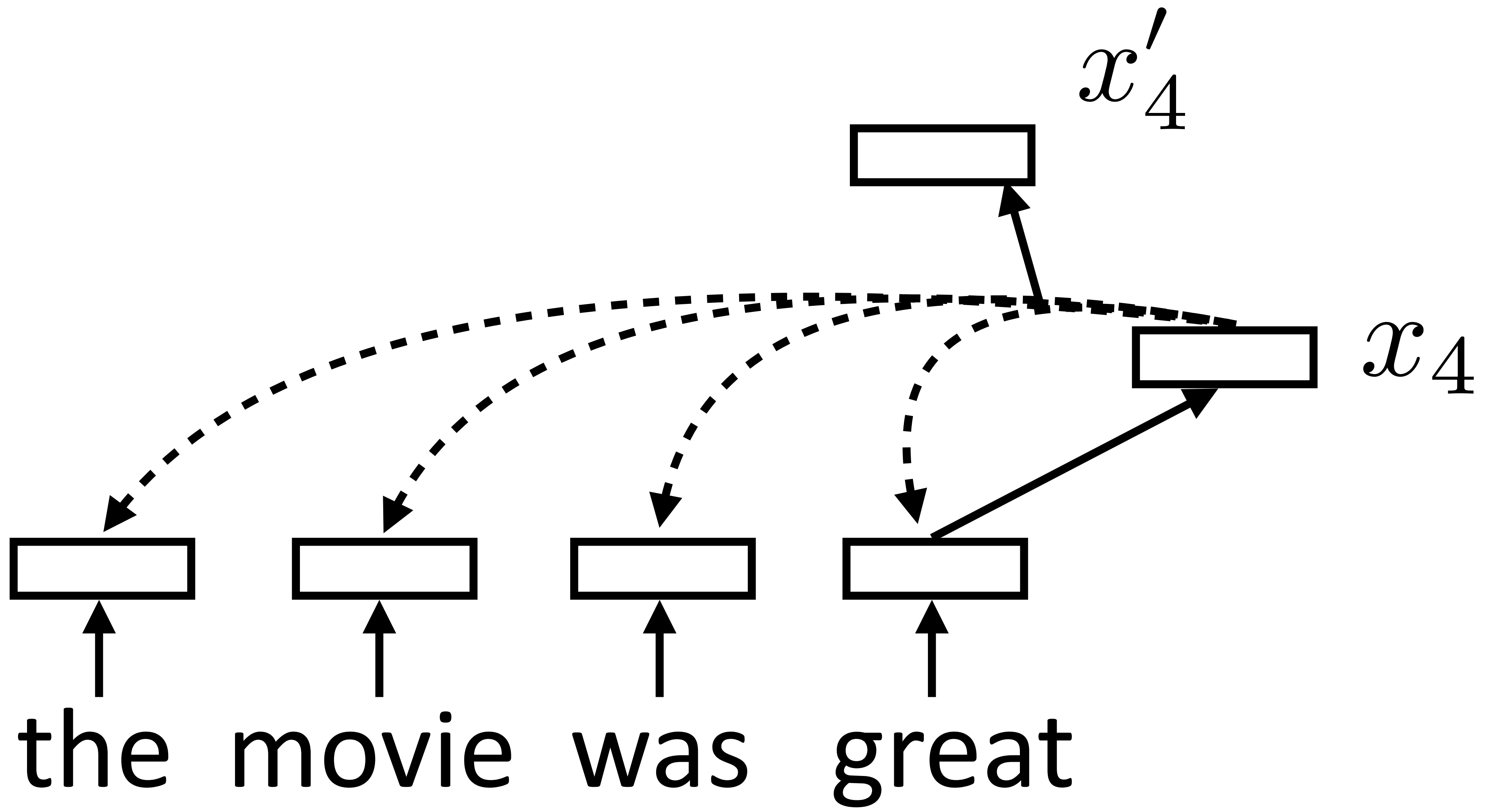

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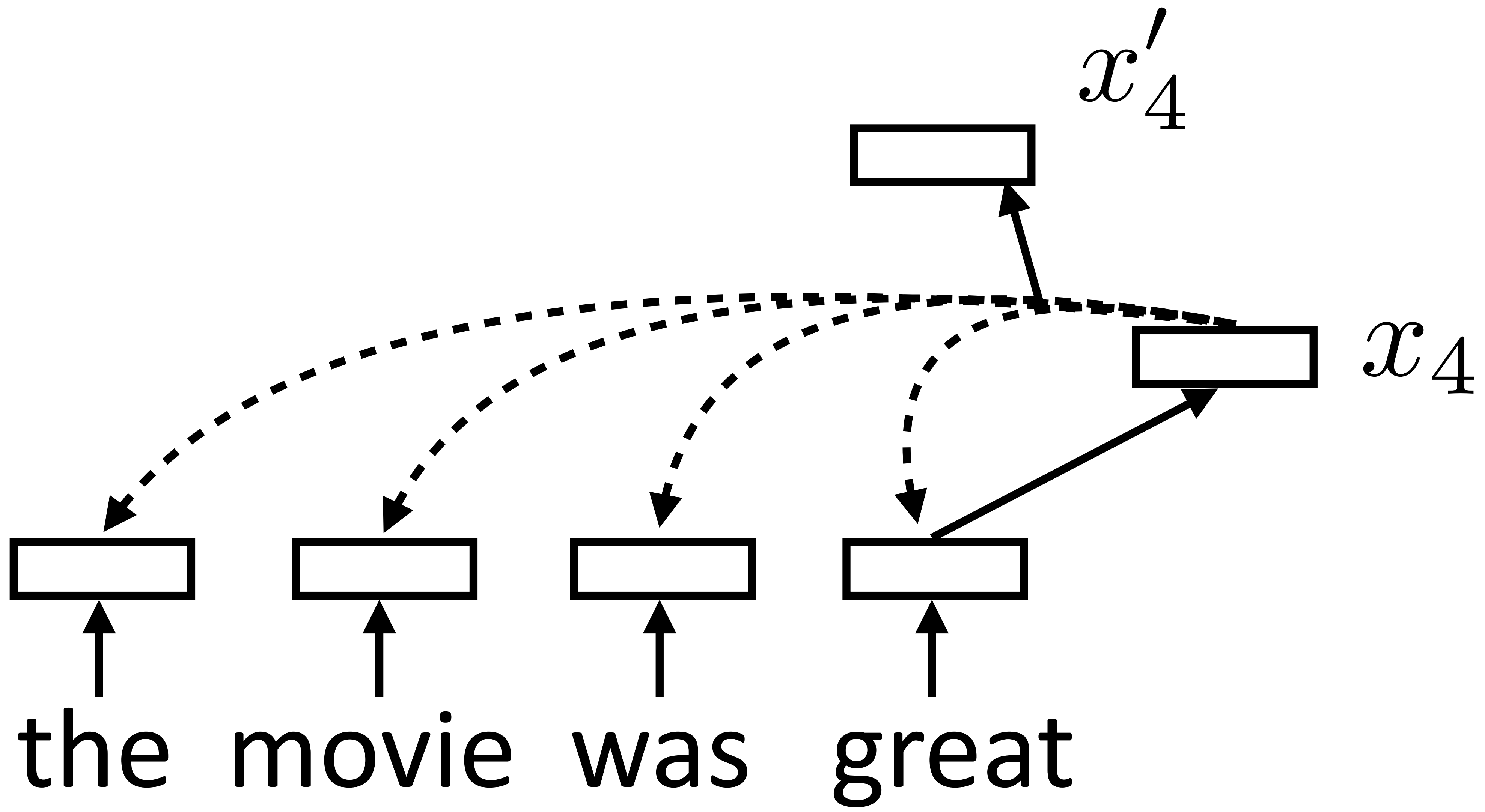

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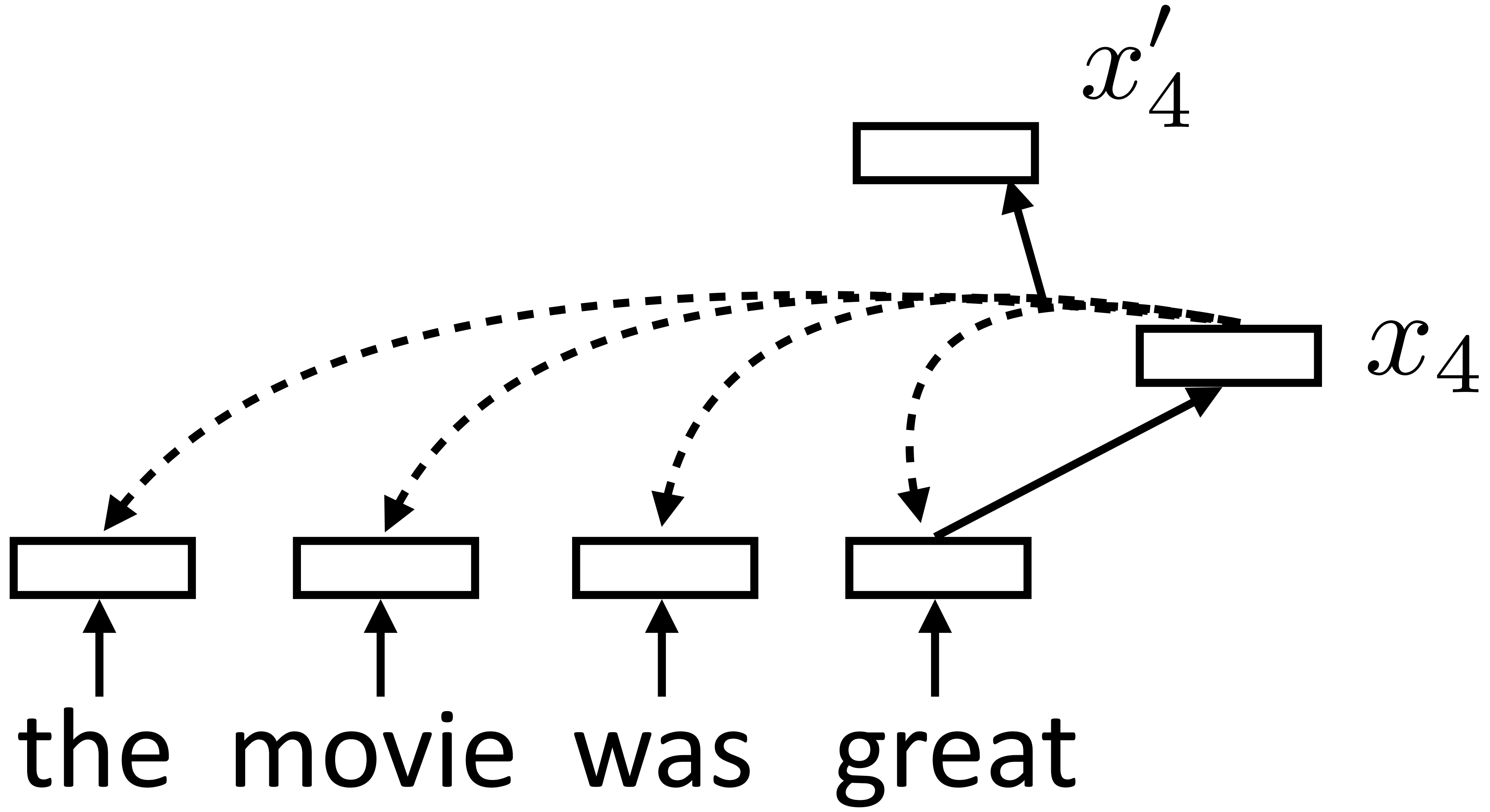

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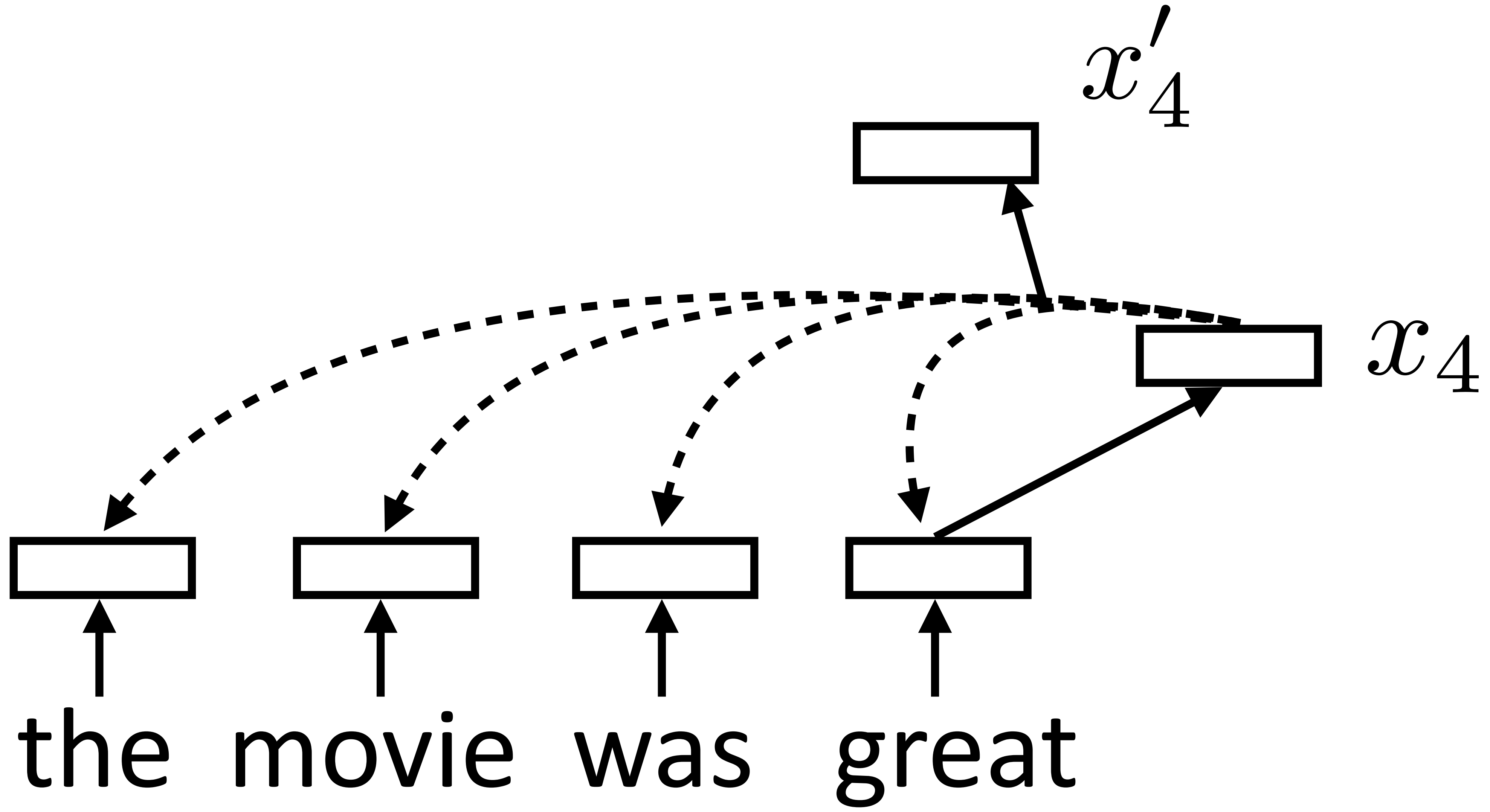

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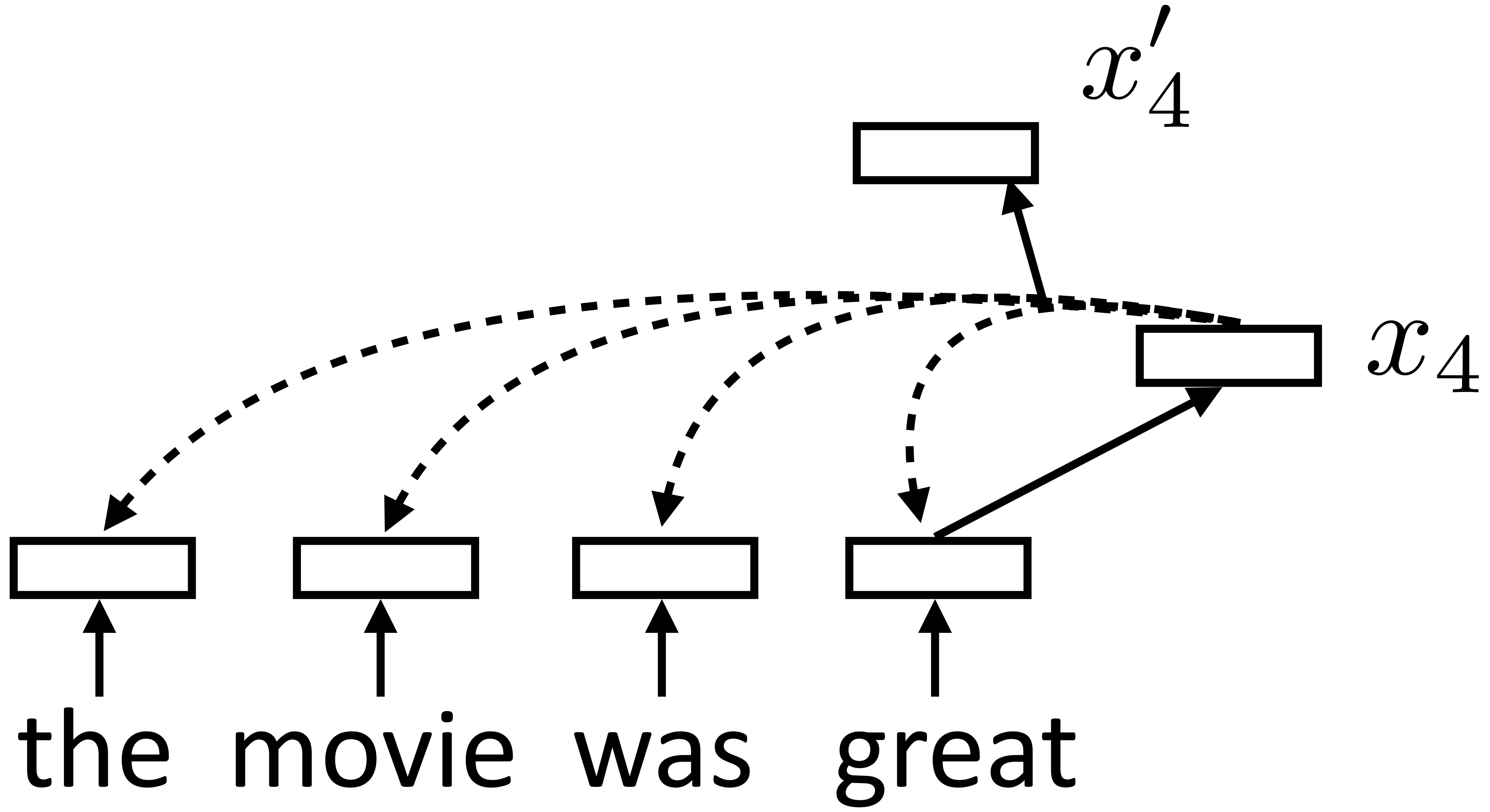

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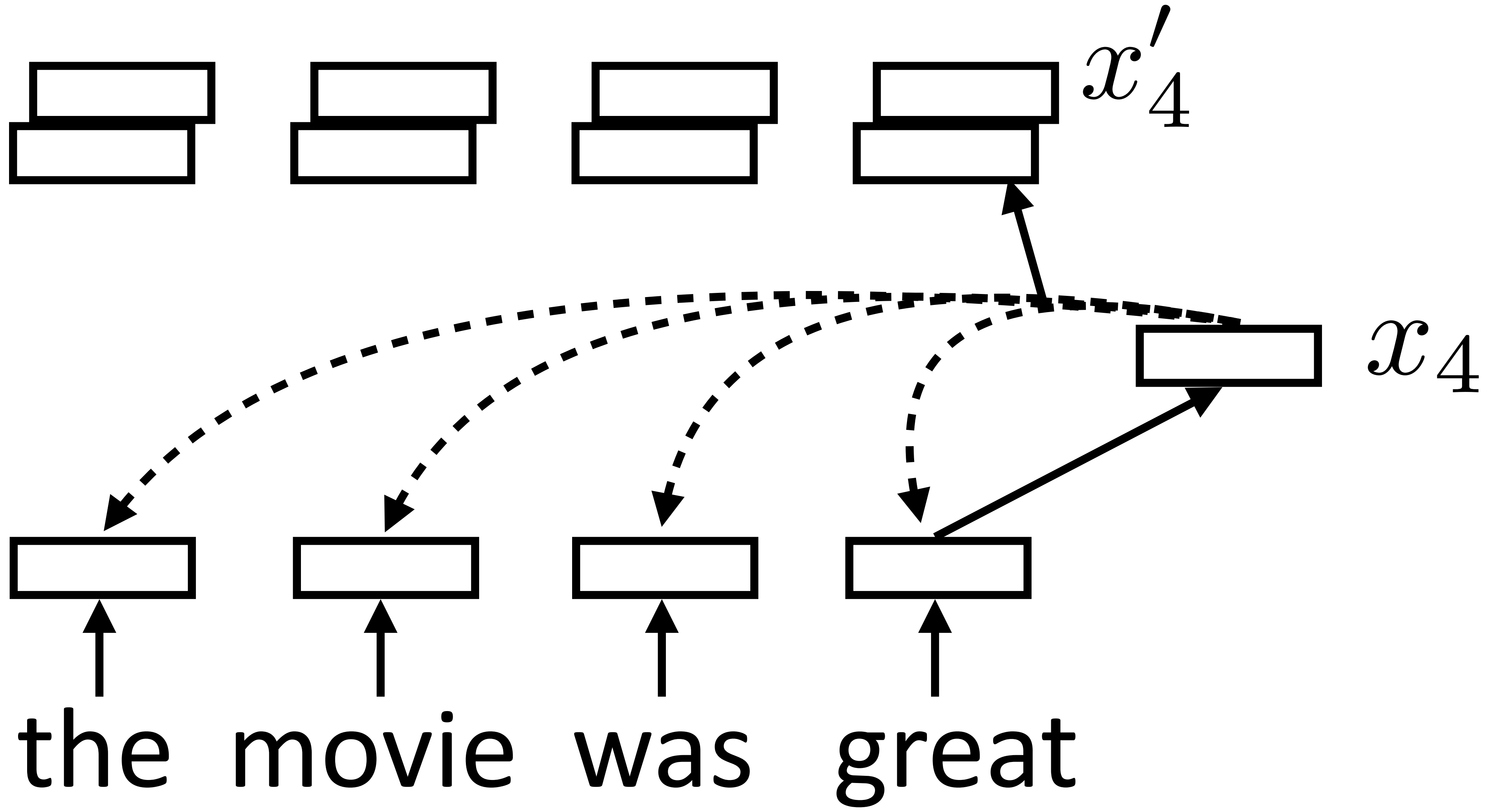

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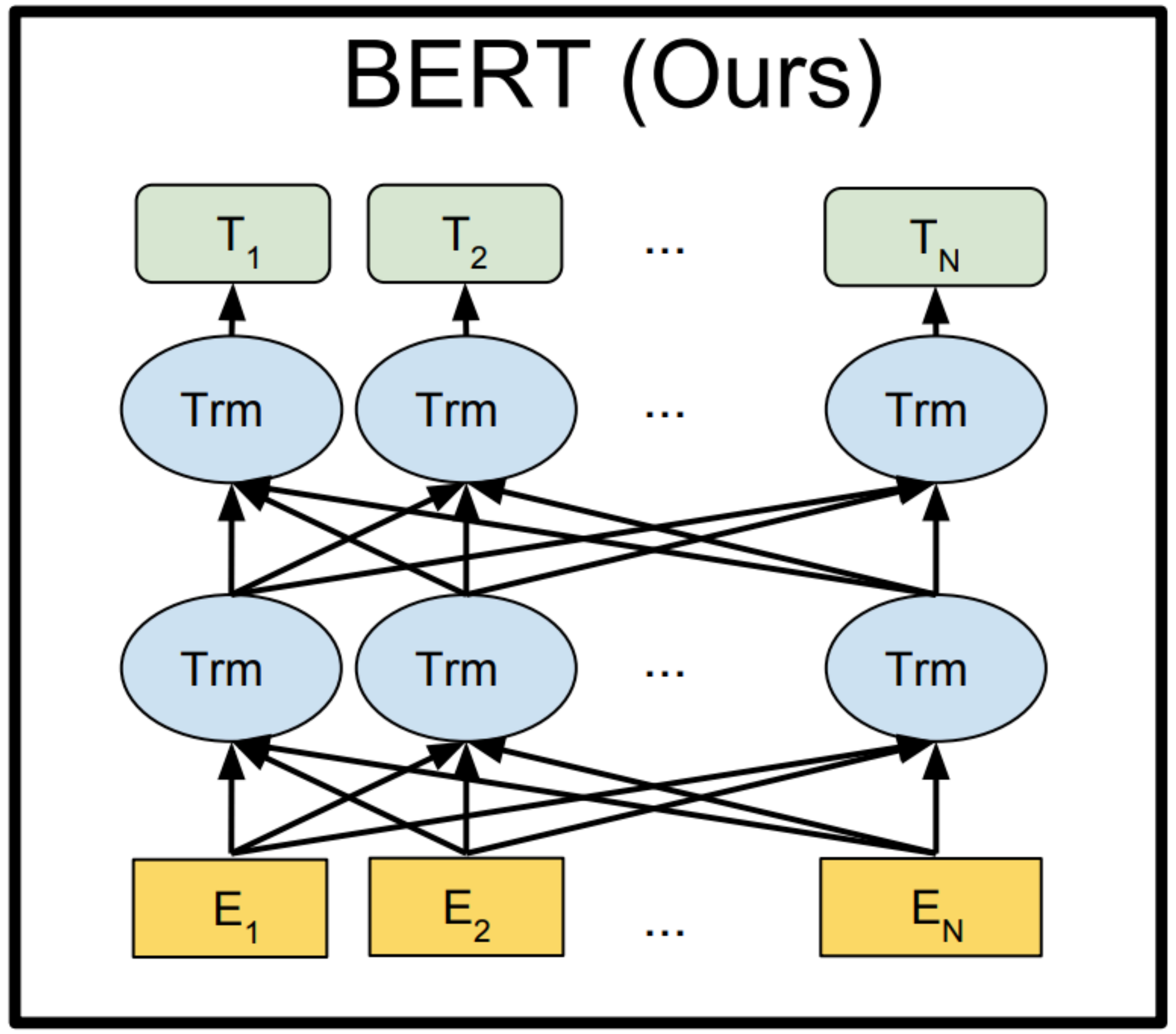

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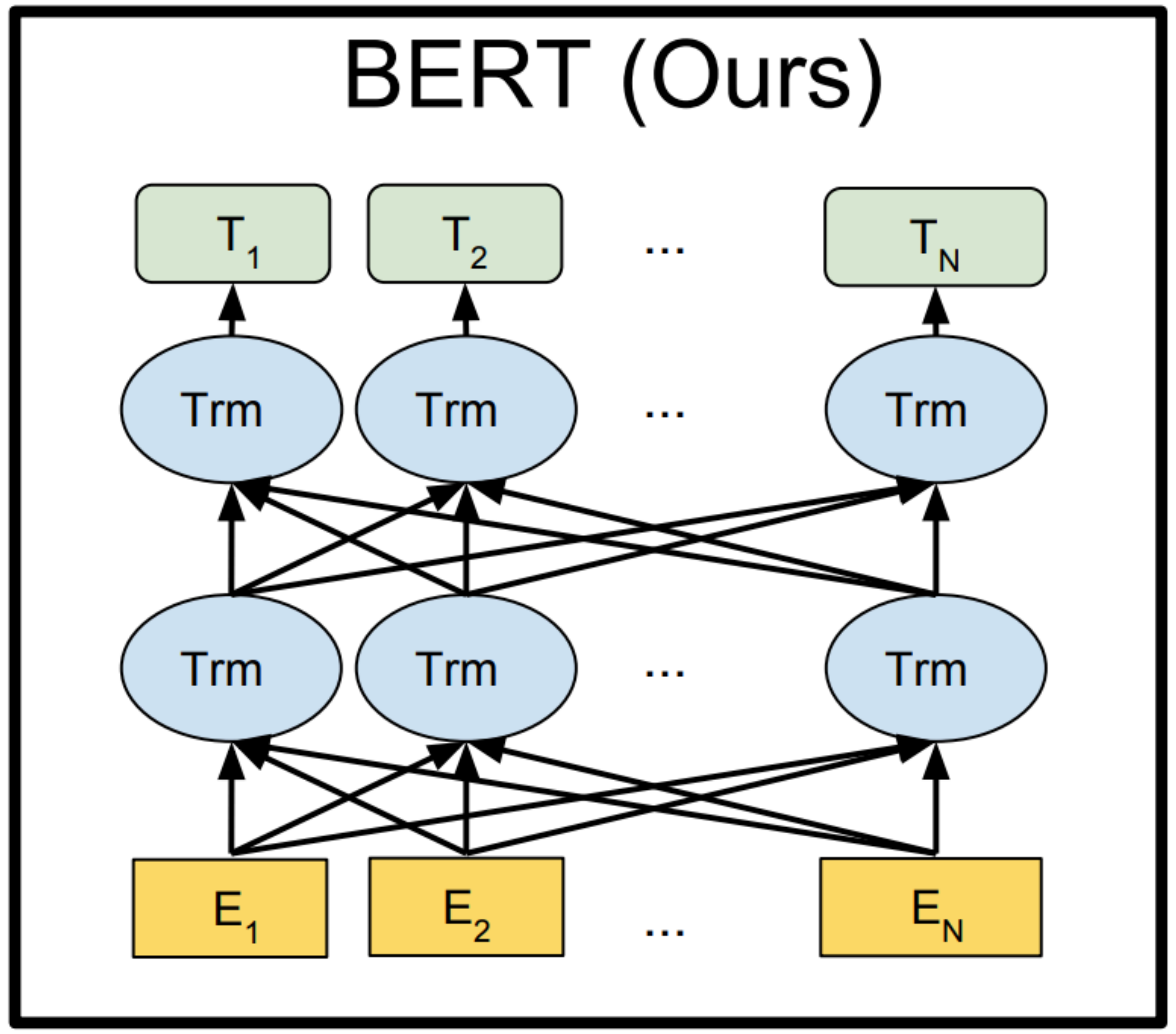

- Stronger than similar methods, SOTA on ~11 tasks (including NER — 92.8 F1)

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

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