CS388: Natural Language Processing

Lecture 16: Seq2seq II

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Administrivia

- Nazneen Rajani (Salesforce) talk this Friday at 11am in 6.302
  Leveraging Explanations for Performance and Generalization in NLP and RL

- Final project feedback posted

- Mini 2 results:
  - Sundara Ramachandran: 82.1%
    - Bidirectional LSTM, 2x256, 300d vectors, 4 epochs x 50 batch size
  - Neil Patil: 80.9%, Qinqin Zhang: 80.7% (CNN), Shivam Garg: 80.1%, Prateek Chaudhry: 80.0%, Abheek Ghosh: 80.0%
    - Fine-tuning embeddings helps, 100-300d LSTM

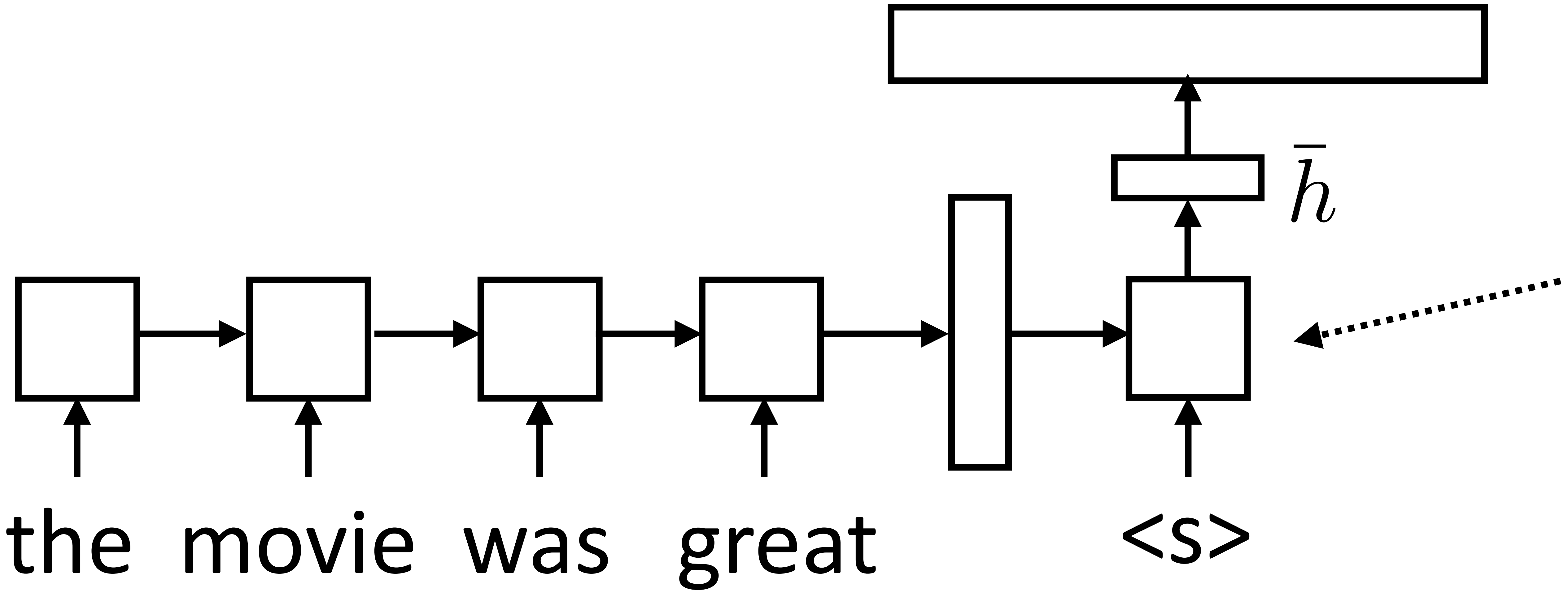
Recall: Seq2seq Model

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

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

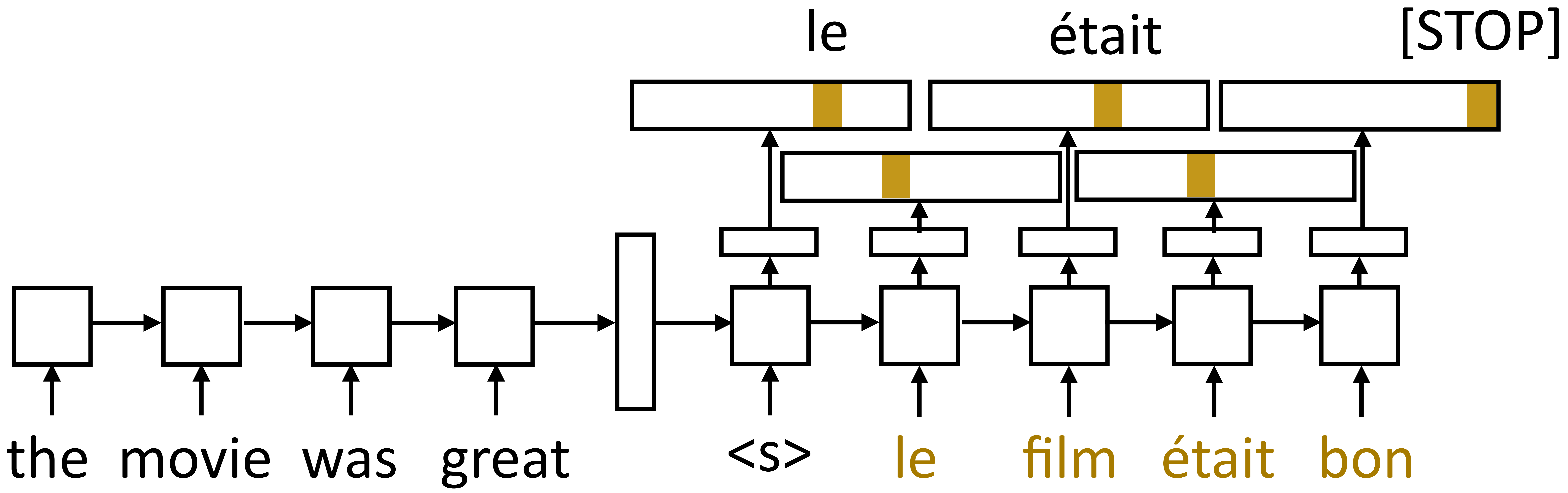
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h})$$

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



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

Recall: Seq2seq Training



- Objective: maximize $\sum_{(\mathbf{x},\mathbf{y})} \sum_{i=1}^{n} \log P(y_i^* | \mathbf{x}, y_1^*, \ldots, y_{i-1}^*)$
- Teacher forcing: feed the correct word regardless of model's prediction (most typical way to train)

Recall: Semantic Parsing as Translation

"what states border Texas"

↓

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

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

Jia and Liang (2015)

This Lecture

- Attention for sequence-to-sequence models
- Copy mechanisms for copying words to the output
- Transformer architecture

Attention

Problems with Seq2seq Models

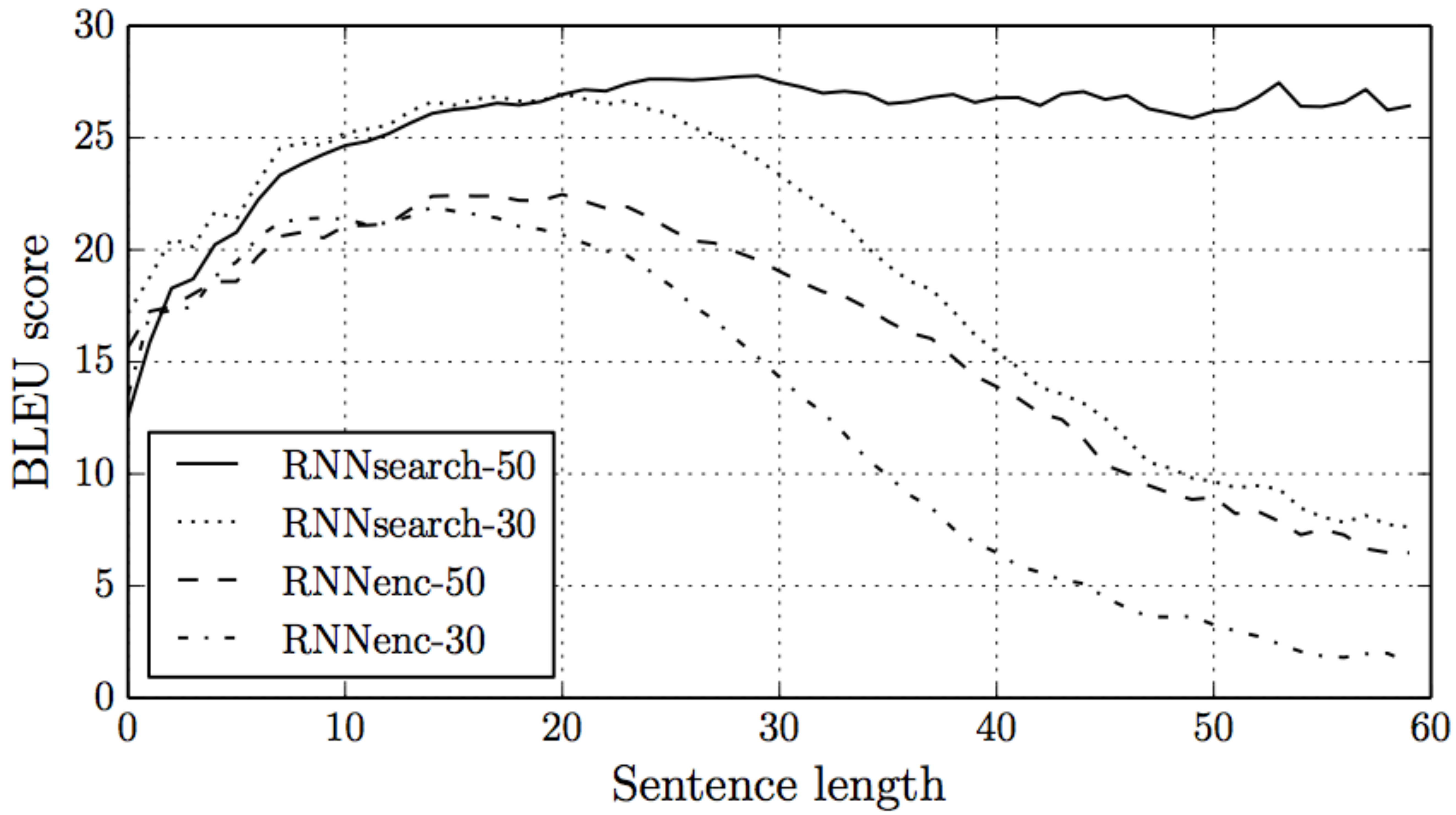
- Encoder-decoder models like to repeat themselves:

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

- Why does this happen?
  - Models trained poorly
  - LSTM state is not behaving as expected so it gets stuck in a "loop" of generating the same output tokens again and again
- Need some notion of input coverage or what input words we've translated

Problems with Seq2seq Models

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



RNNenc: the model we've discussed so far

RNNsearch: uses attention

Bahdanau et al. (2014)

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

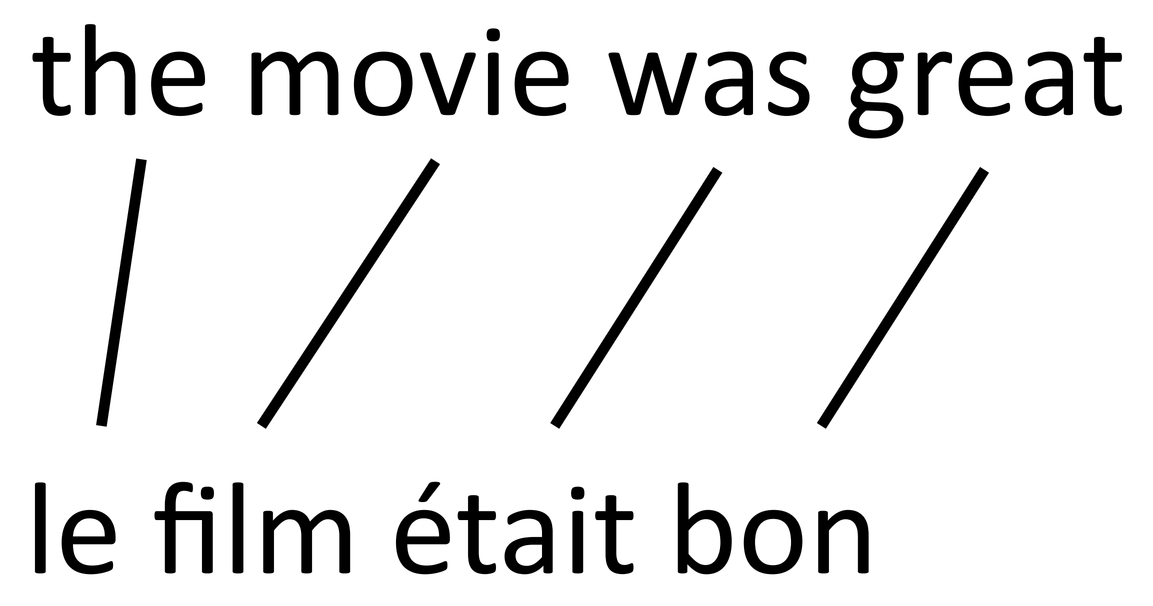
nn: Le unk de unk à unk , . . . [truncated] . . . , a été pris le jeudi matin

- Encoding these rare words into a vector space is really hard
- In fact, we don't want to encode them, we want a way of directly looking back at the input and copying them (*Pont-de-Buis*)

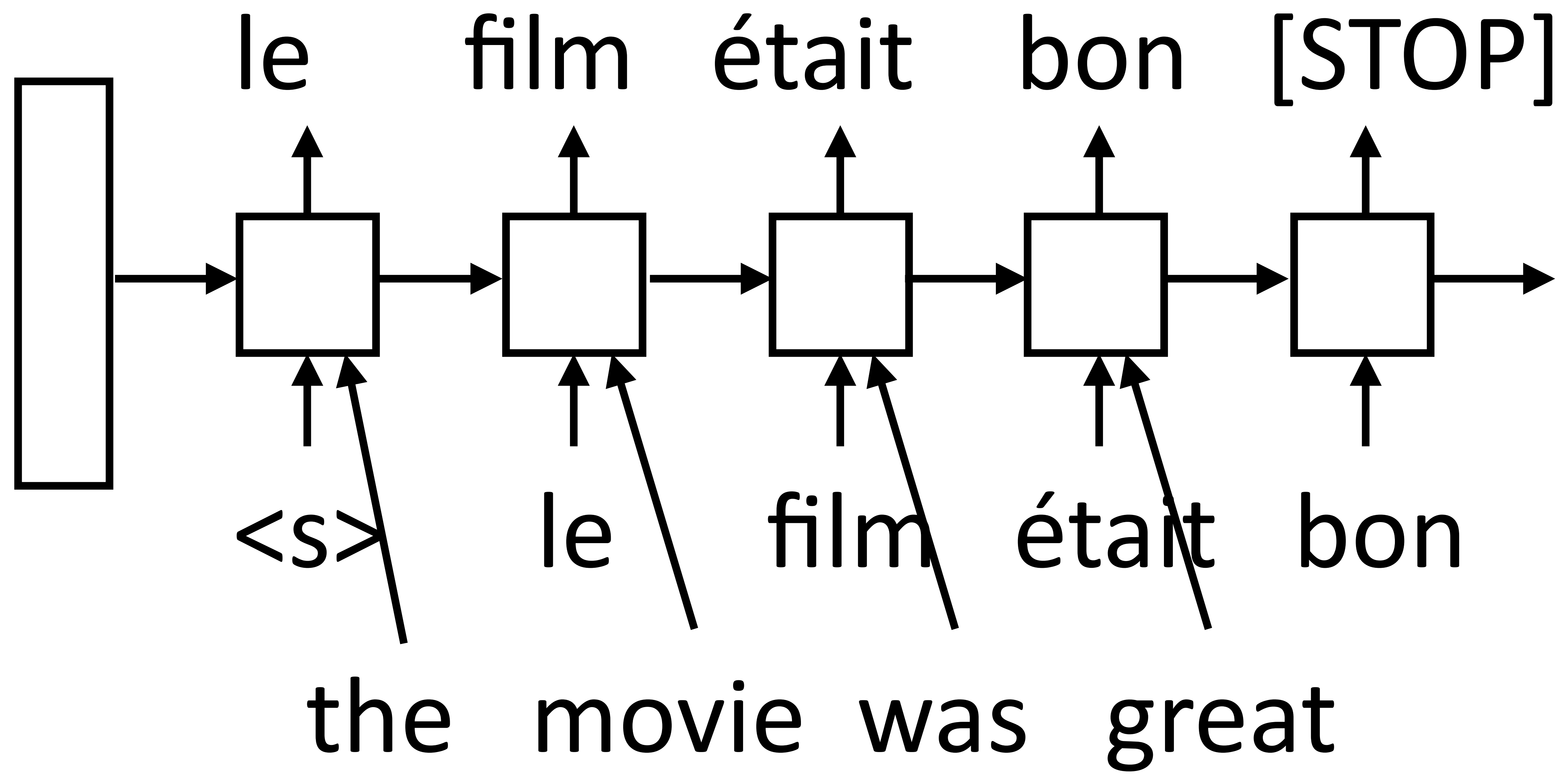
Jean et al. (2015), Luong et al. (2015)

Aligned Inputs

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



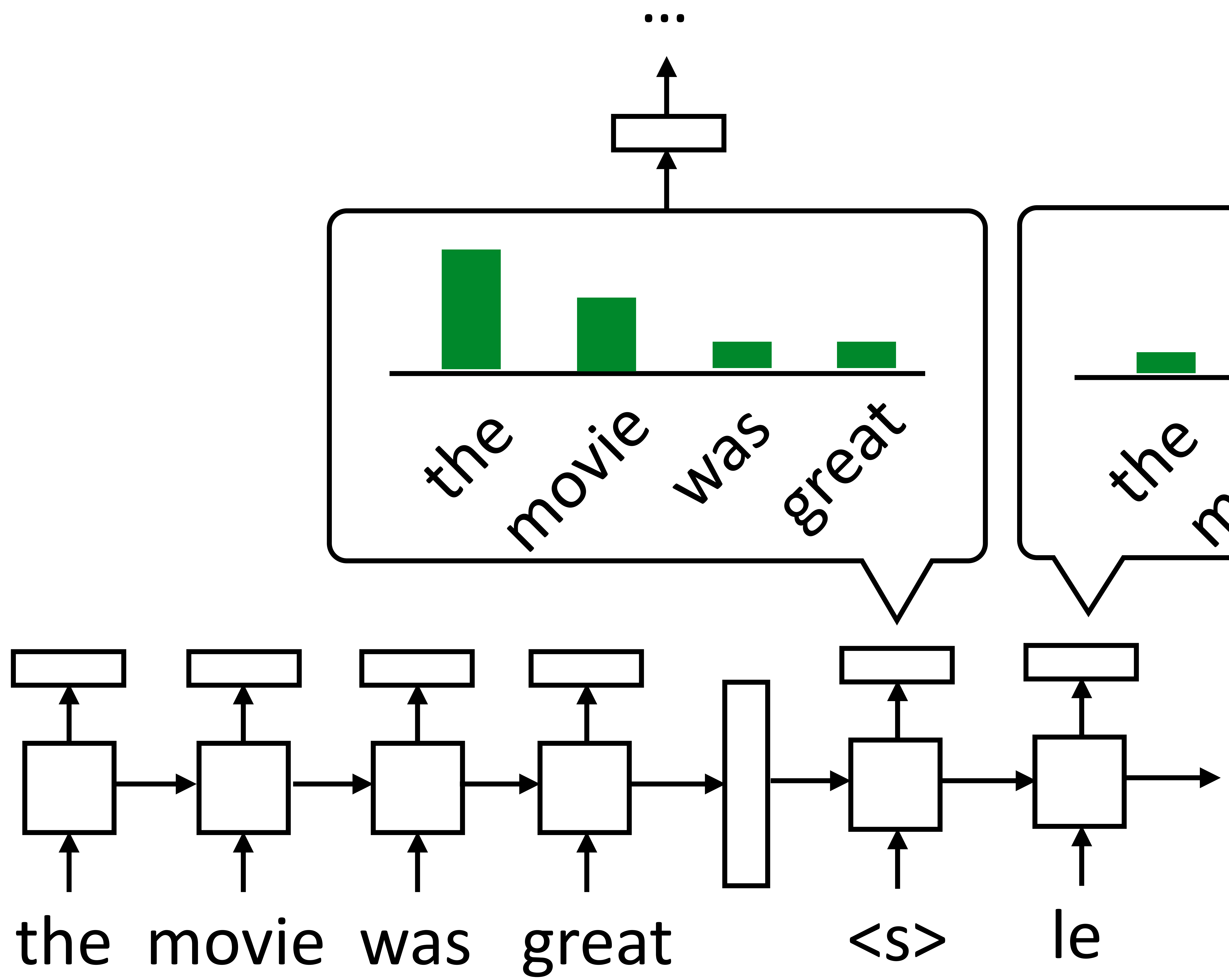
- Can look at the corresponding input word when translating — this could scale!



- Much less burden on the hidden state

- How can we achieve this without hardcoding it?

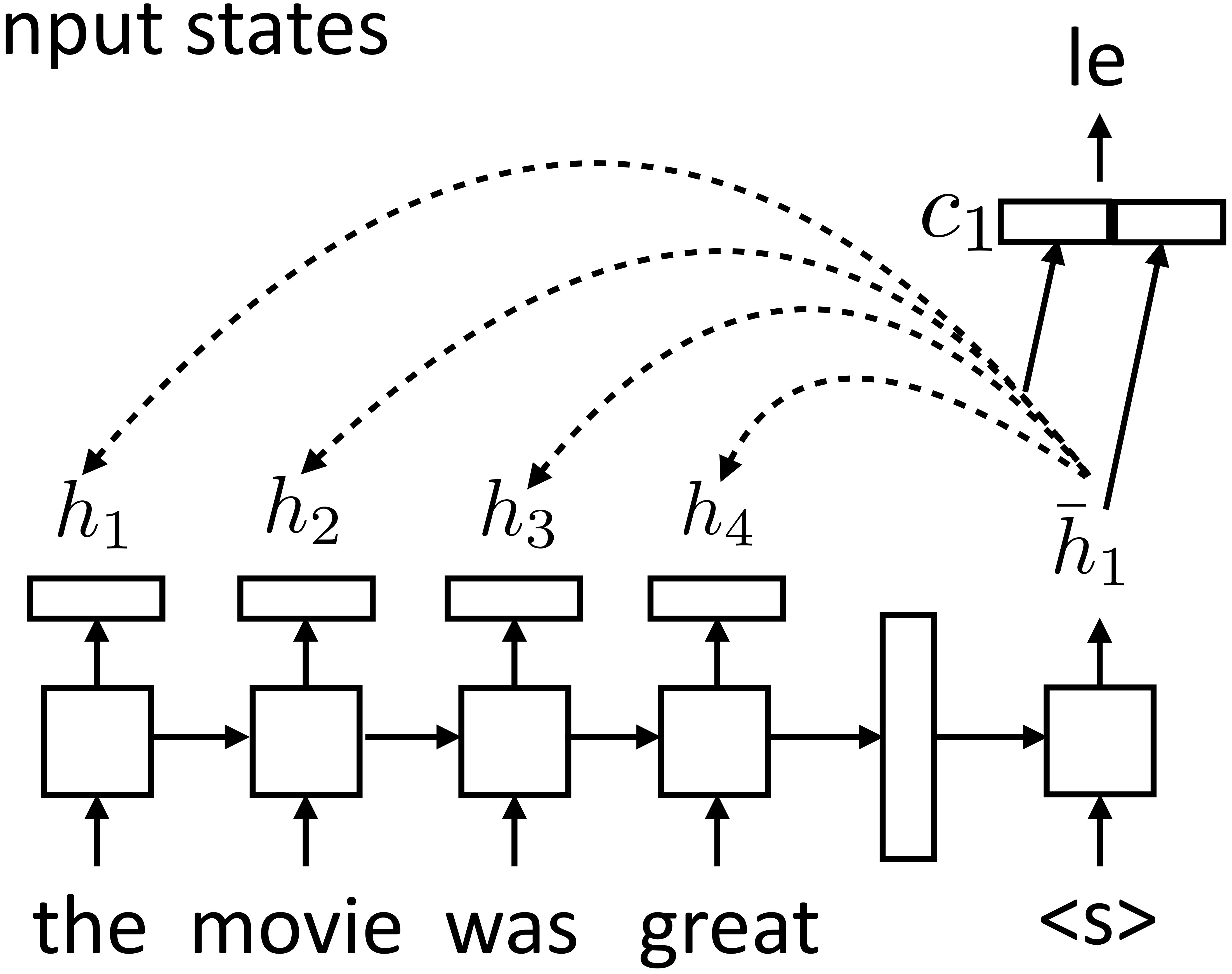
Attention



- 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



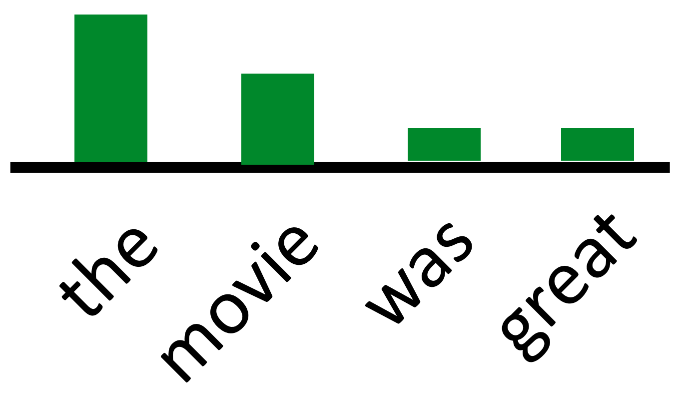
- No attn: $P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W\bar{h}_i)$

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

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

- Weighted sum of input hidden states (vector)

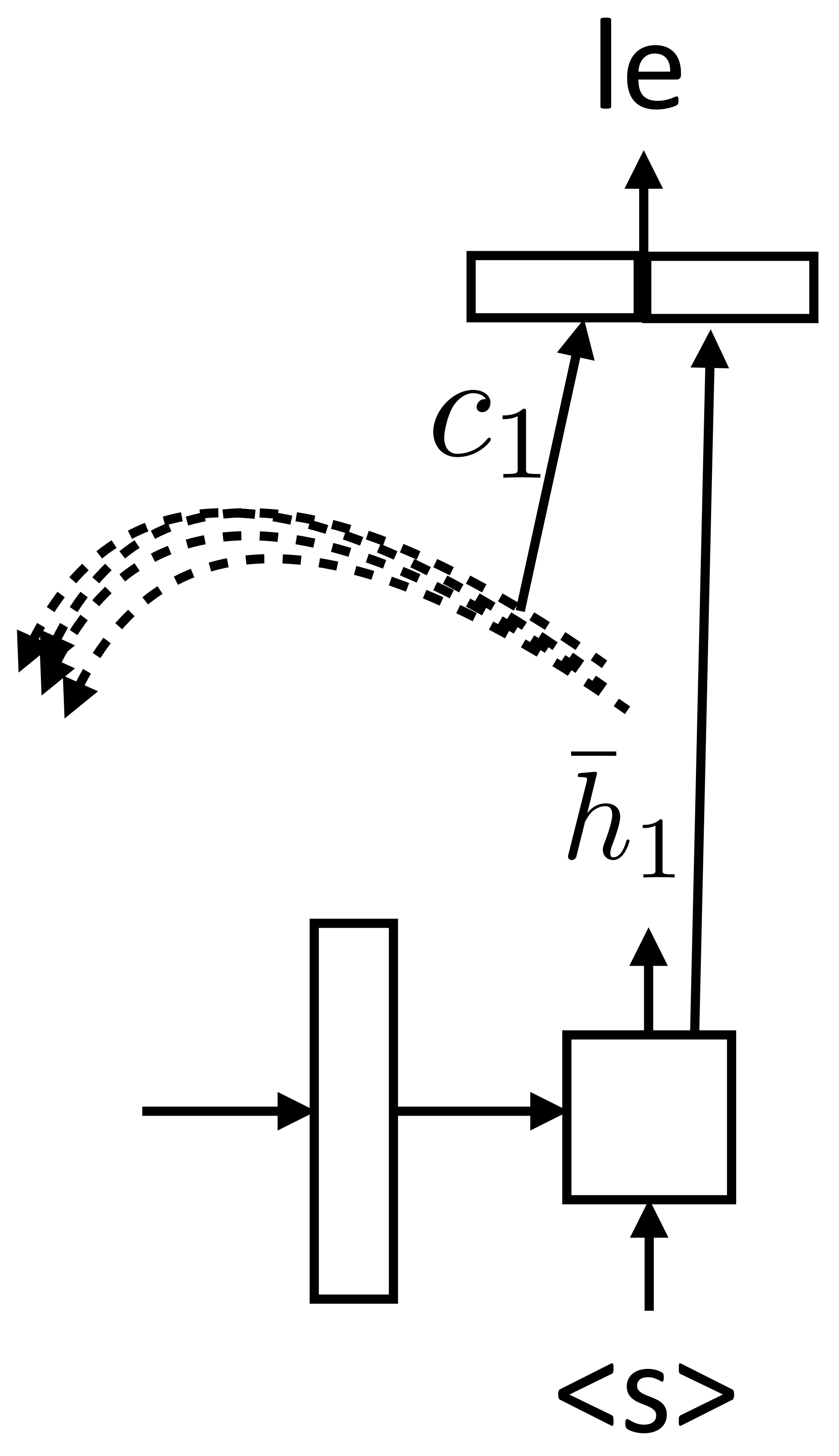
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$



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

- Some function *f* (TBD)

Attention



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

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

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

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

- Bahdanau+ (2014): additive

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

- Luong+ (2015): dot product

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

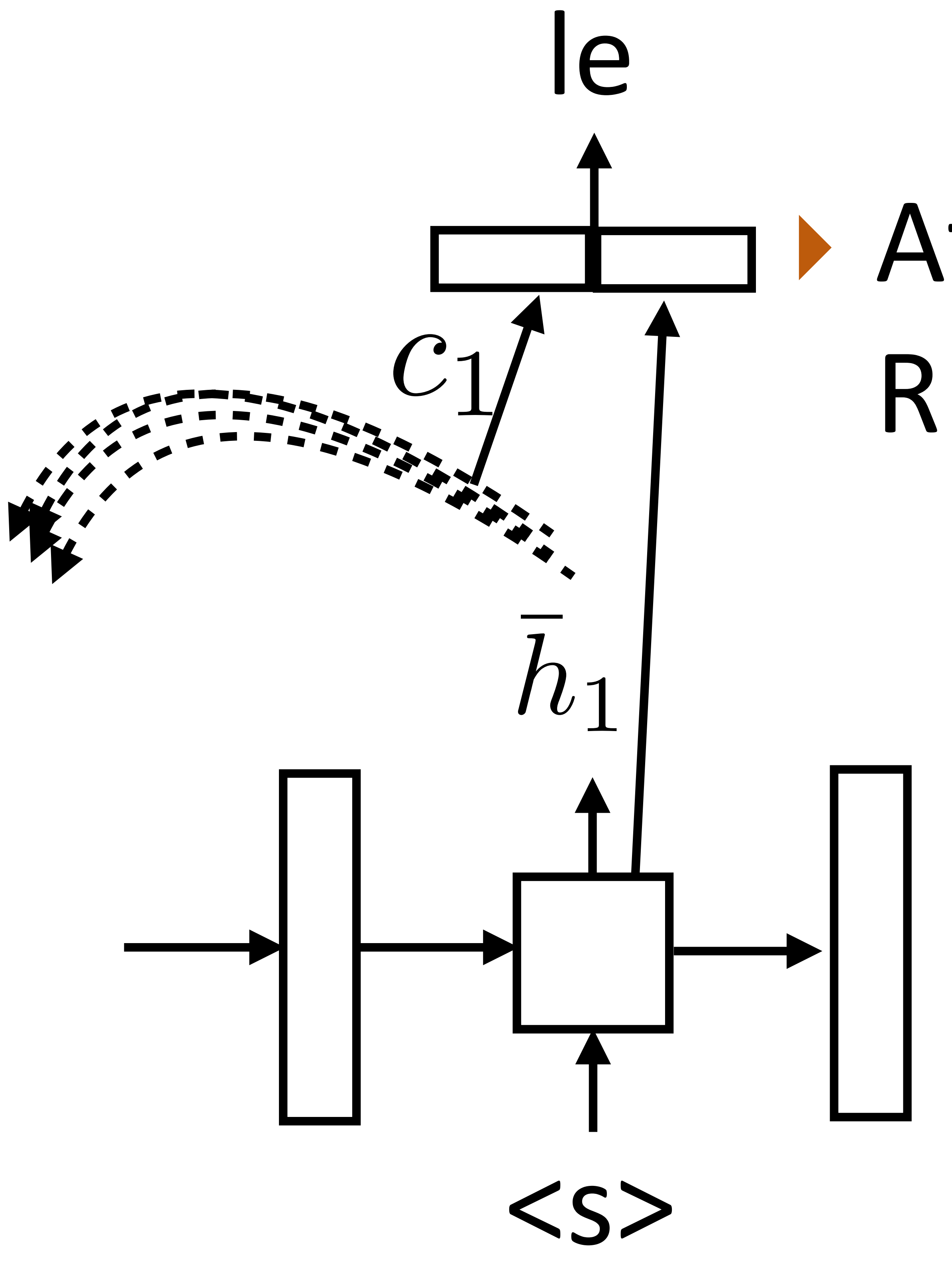
- Luong+ (2015): bilinear

- Note that this all uses outputs of hidden layers

Luong et al. (2015)

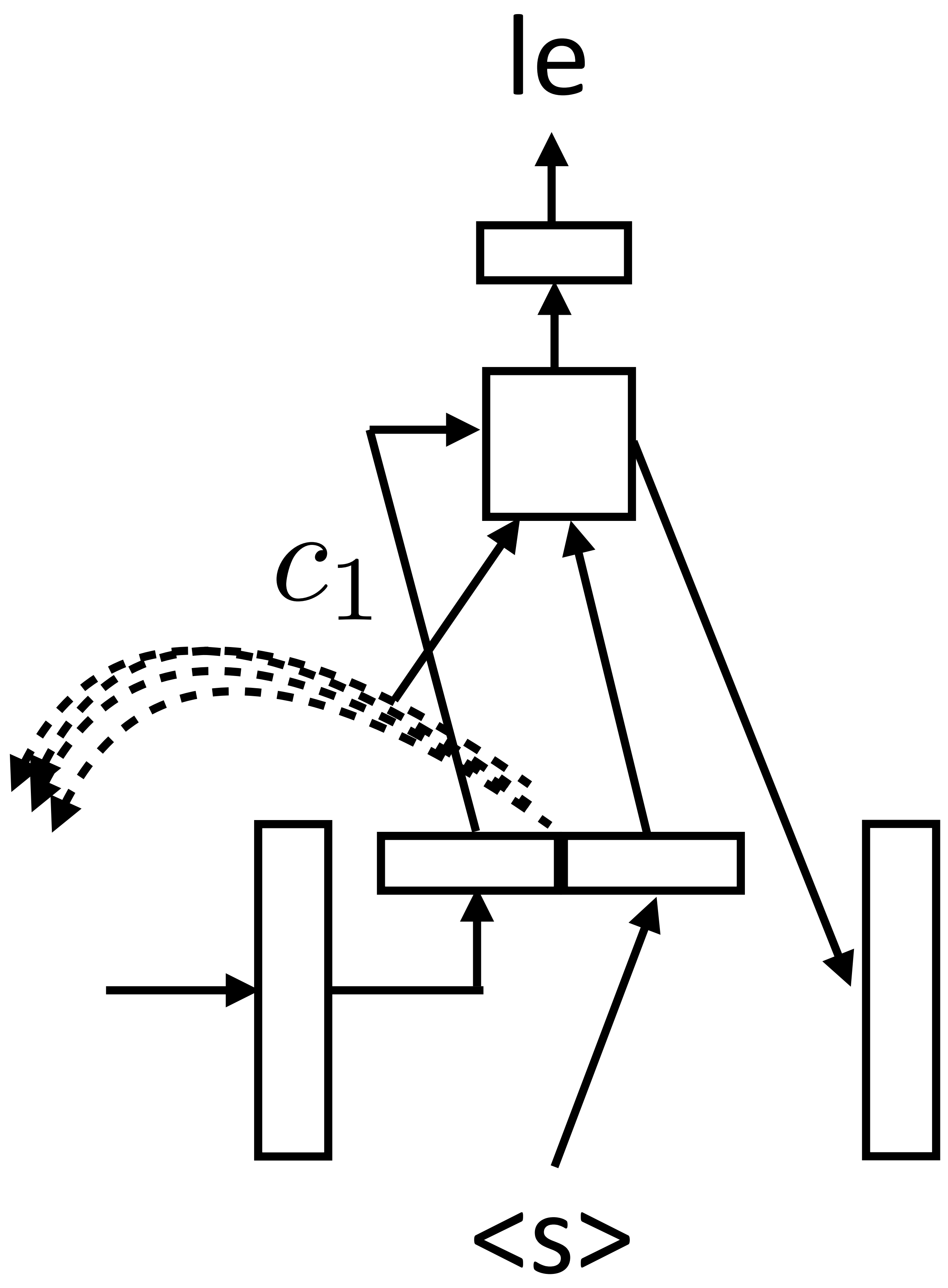
Alternatives

- When do we compute attention? Can compute before or after RNN cell



- After RNN cell

Luong et al. (2015)

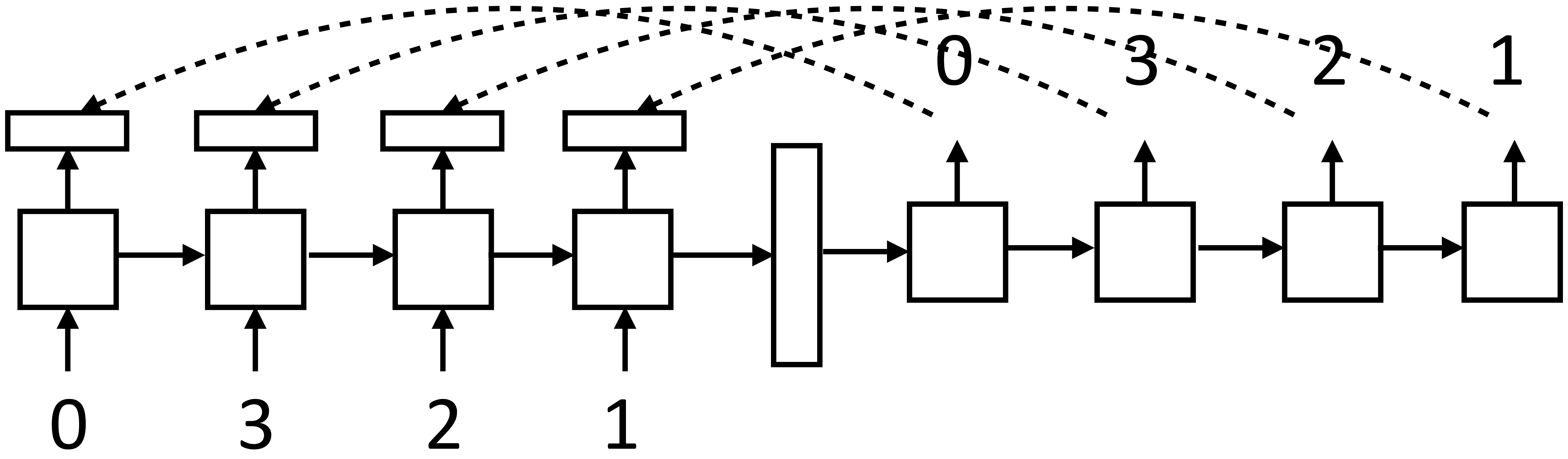


- Before RNN cell; this one is a little more convoluted and less standard

Bahdanau et al. (2015)

What can attention do?

- Learning to copy — how might this work?



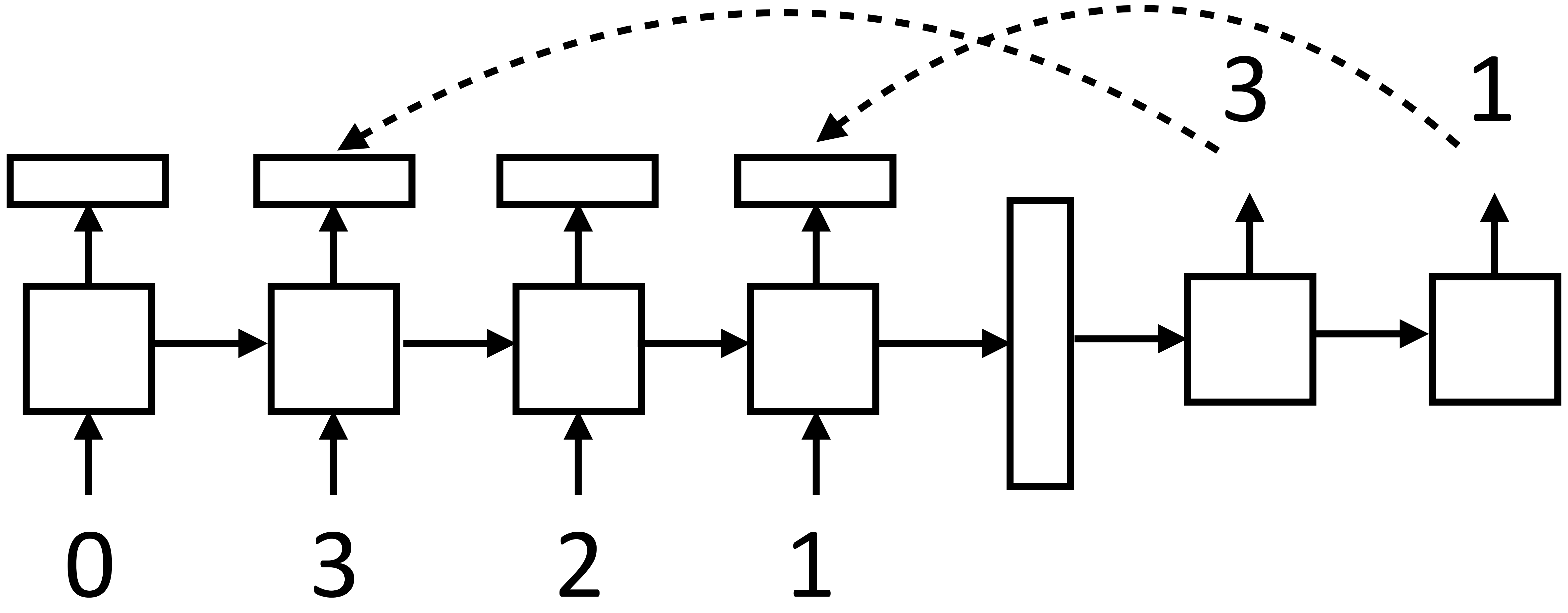
- LSTM can learn to count with the right weight matrix

- This is a kind of position-based addressing

Luong et al. (2015)

What can attention do?

- Learning to subsample tokens



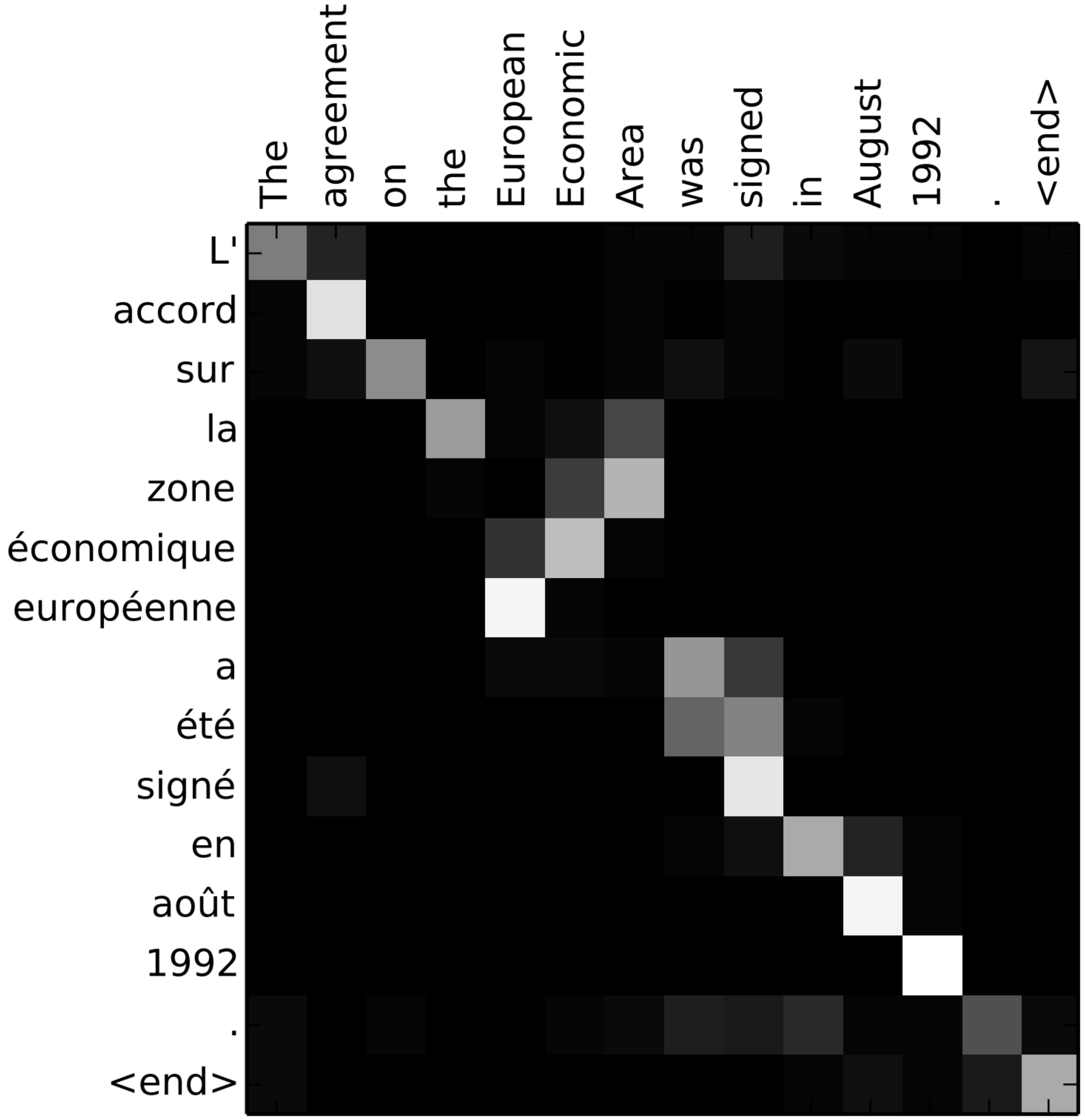
- Need to count (for ordering) and also determine which tokens are in/out

- Content-based addressing

Luong et al. (2015)

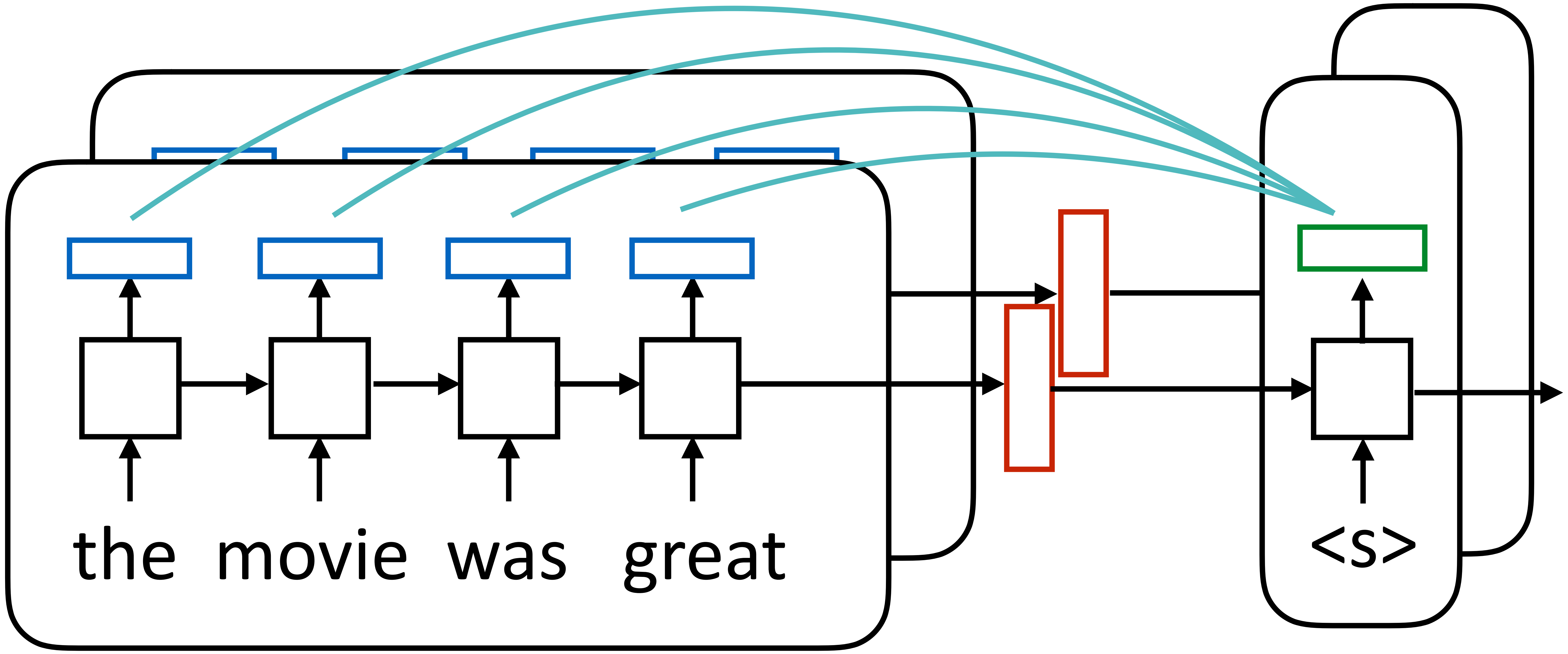
Attention

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



Batching Attention

token outputs: batch size x sentence length x hidden size



hidden state: batch size x hidden size

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

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

sentence outputs: batch size x hidden size

attention scores = batch size x sentence length

c = batch size x hidden size

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

- Make sure tensors are the right size!

Luong et al. (2015)

Results

- Machine translation: BLEU score of 14.0 on English-German -> 16.8 with attention, 19.0 with smarter attention (we'll come back to this later)

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

- Semantic parsing: ~30-50% accuracy -> 70+% accuracy on Geoquery

Luong et al. (2015)
Chopra et al. (2016)
Jia and Liang (2016)

Copying Input/Pointers

Unknown Words

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

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

from attention

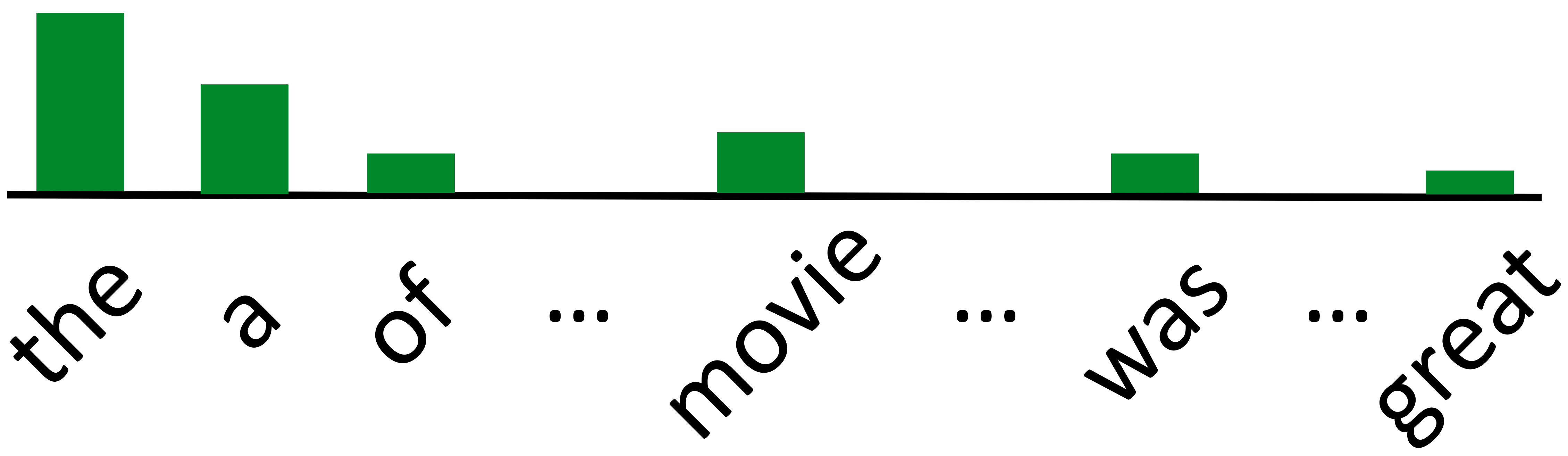
from RNN hidden state

- Problems: target word has to be in the vocabulary, attention + RNN need to generate good embedding to pick it

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

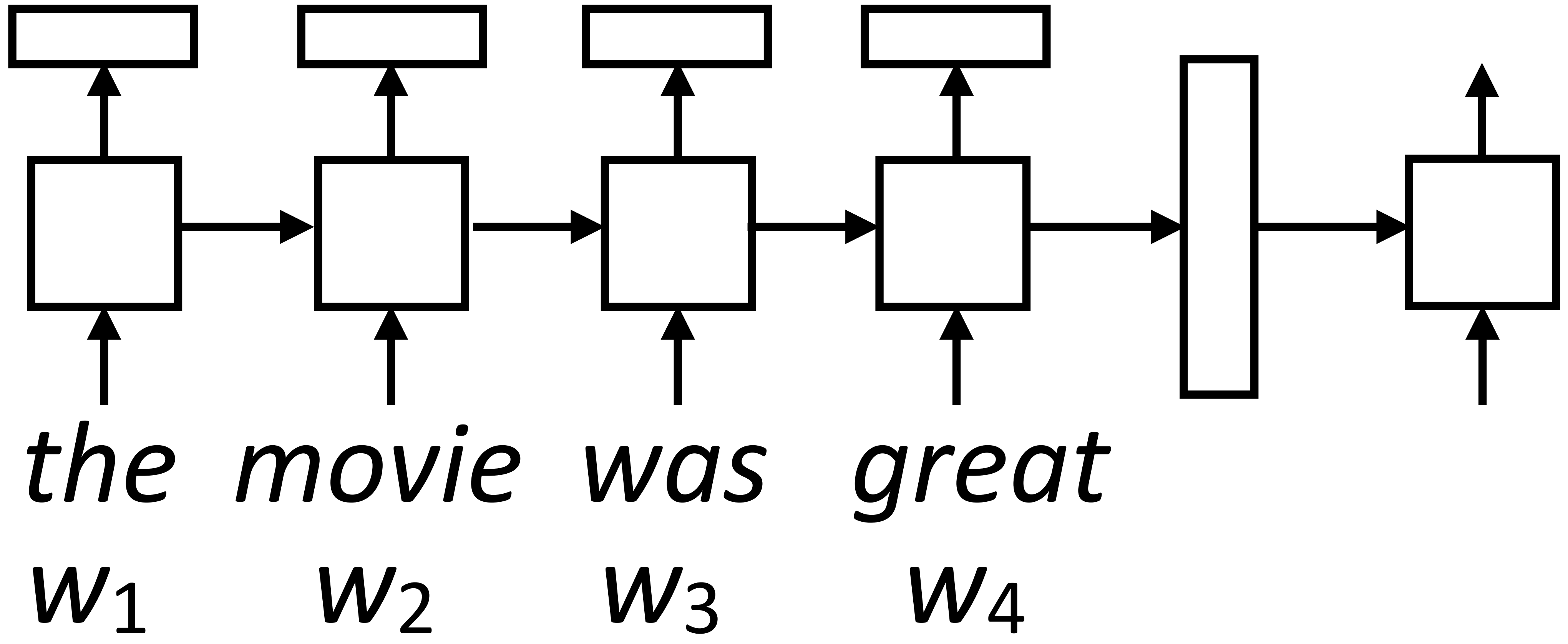
Pointer Networks

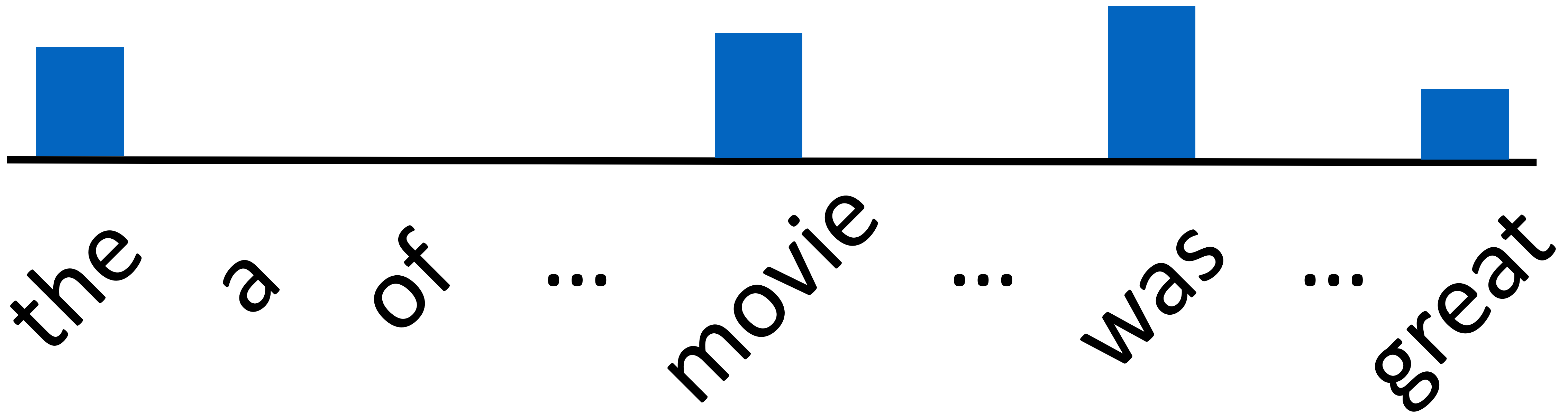
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$



- Standard decoder (P_{vocab}): softmax over vocabulary, all words get >0 prob
- Pointer network: predict from *source words* instead of *target vocab*

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



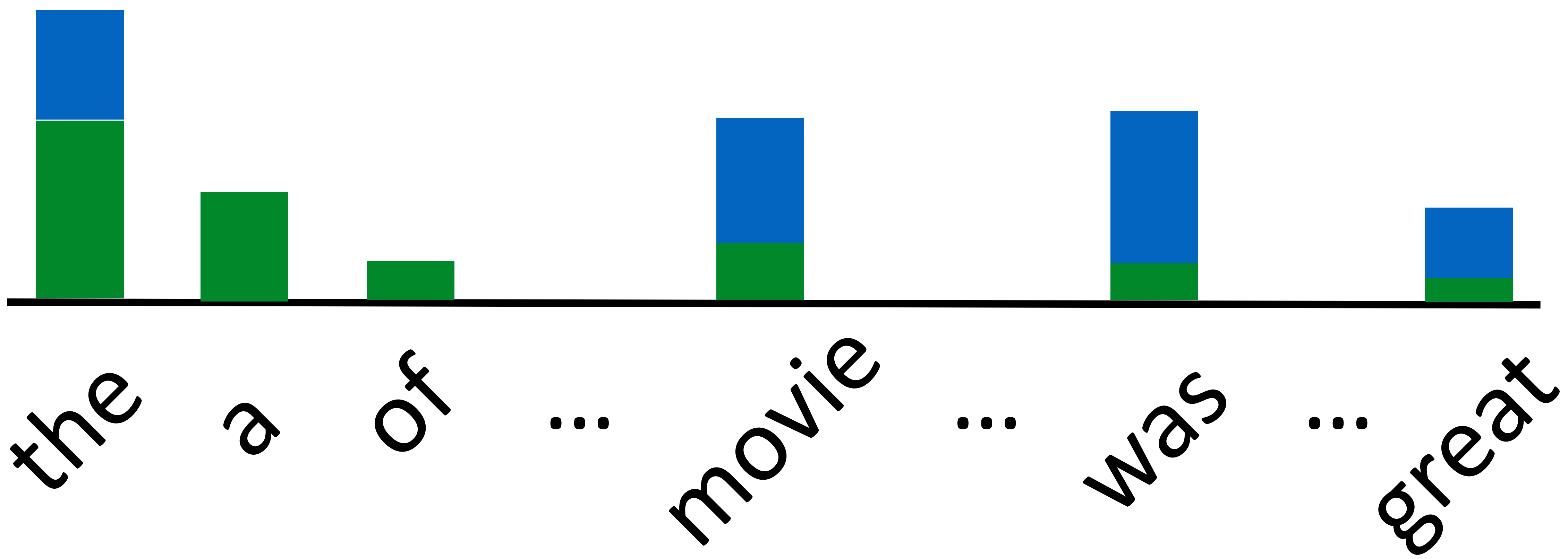


Pointer Generator Mixture Models

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

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

- Predict *P*(copy) based on decoder state, input, etc.
- Marginalize over copy variable during training and inference
- Model will be able to both generate and copy, flexibly adapt between the two



Copying

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

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

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

- Some words we may want to copy may not be in the fixed output vocab (*Pont-de-Buis*)

- Solution: expand the vocabulary dynamically. New words can only be predicted by copying (always 0 probability under P_{vocab})

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

Results

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

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

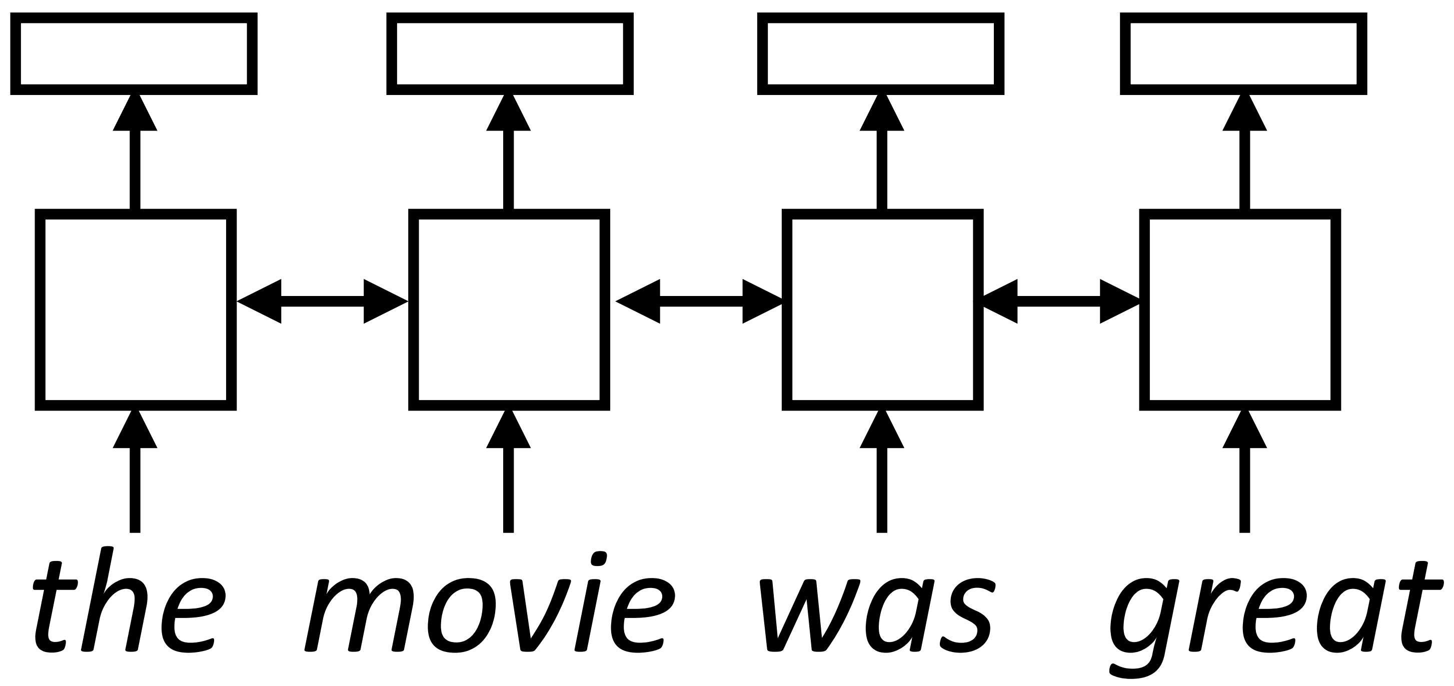
- Copying typically helps a bit, but attention captures most of the benefit. However, vocabulary expansion is critical for some tasks (machine translation)

Jia and Liang (2016)

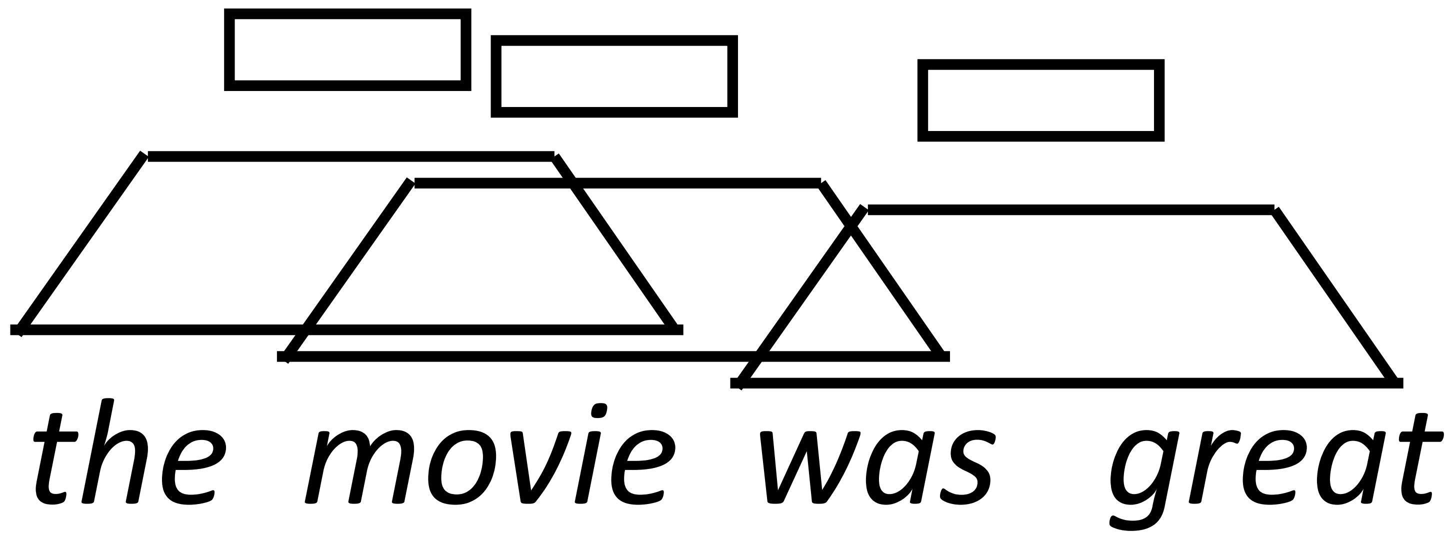
Transformers

Sentence Encoders

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



- CNNs do something similar with filters



- Attention can give us a third way to do this

Vaswani et al. (2017)

Self-Attention

- Assume we're using GloVe — what do we want our neural network to do?

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

- What words need to be contextualized here?
  - Pronouns need to look at antecedents
  - Ambiguous words should look at context
  - Words should look at syntactic parents/children
- Problem: LSTMs and CNNs don't do this

Vaswani et al. (2017)

Self-Attention

- Want:

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

- LSTMs/CNNs: tend to look at local context

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

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

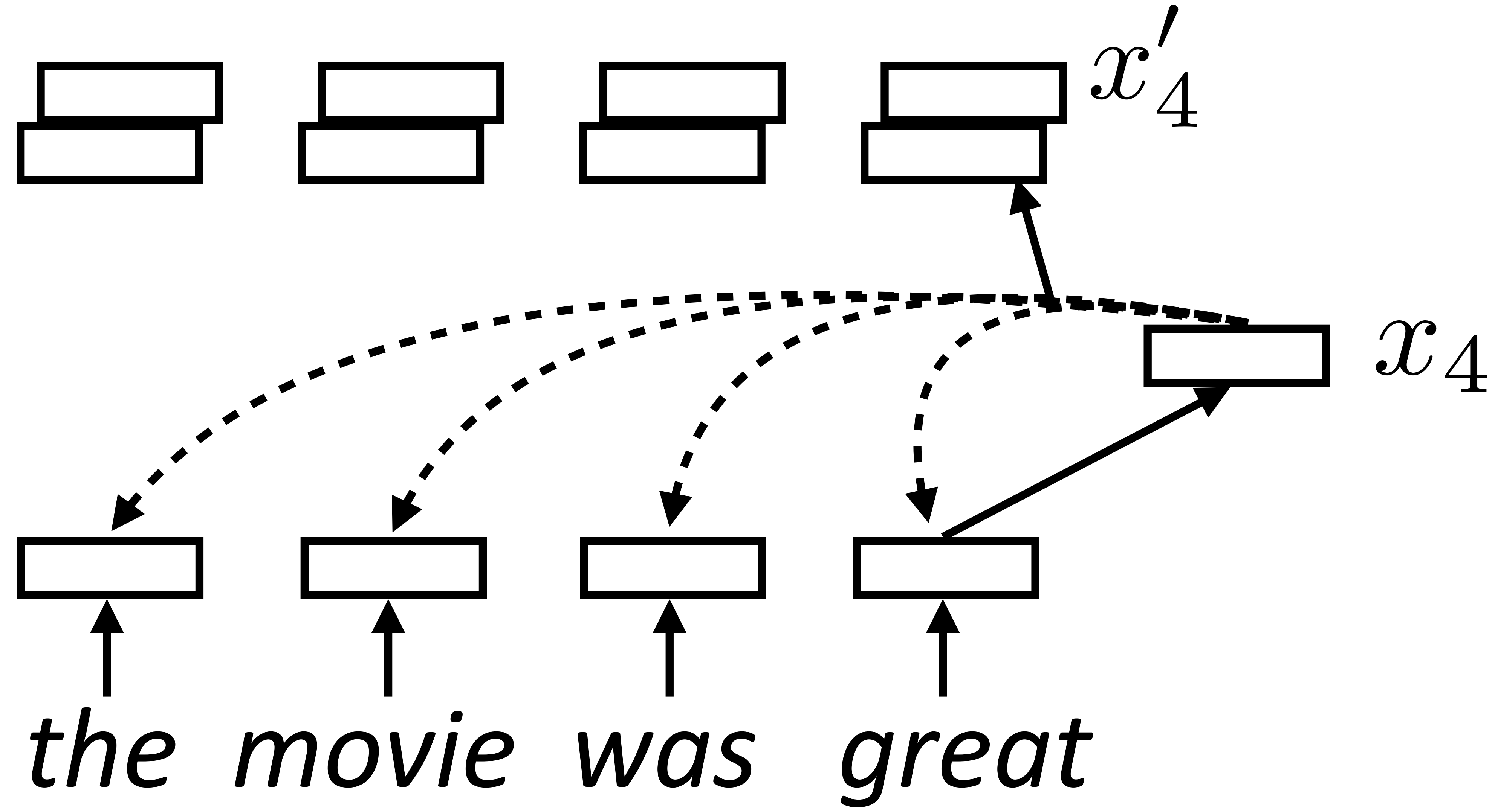
Vaswani et al. (2017)

Self-Attention

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

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

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



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

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

Vaswani et al. (2017)

What can self-attention do?

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

0	0.5	0	0	0.1	0.1	0	0.1	0.2	0	0	0
0	0.1	0	0	0	0	0	0	0.5	0	0.4	0

- Attend nearby + to semantically related terms
- This is a demonstration, we will revisit what these models actually learn when we discuss BERT
- Why multiple heads? Softmaxes end up being peaked, single distribution cannot easily put weight on multiple things

Vaswani et al. (2017)

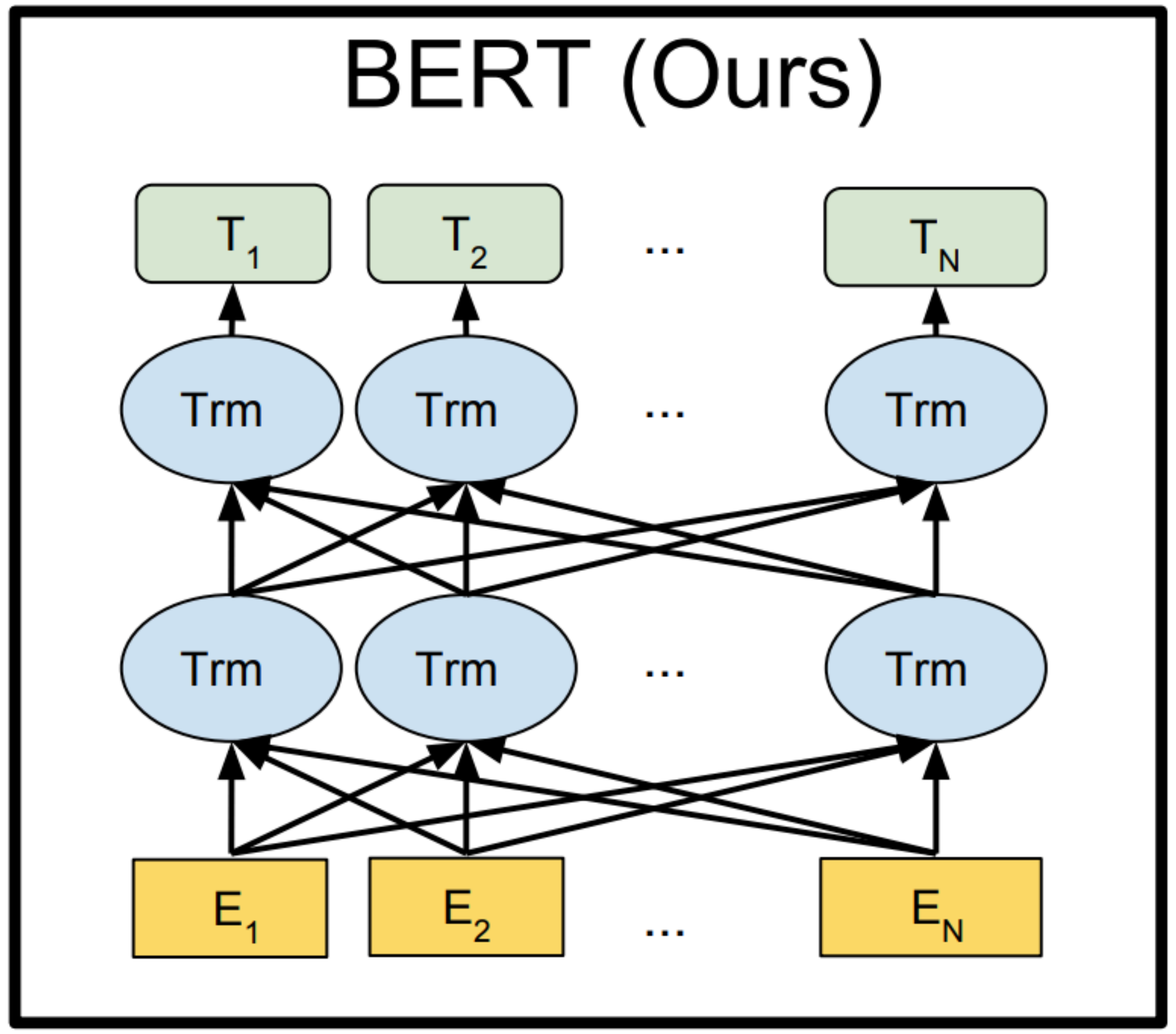
Transformer Uses

- Supervised: transformer can replace LSTM as encoder, decoder, or both; will revisit this when we discuss MT

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

- BERT (Bidirectional Encoder Representations from Transformers): pretraining transformer language models similar to ELMo

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



Takeaways

- Attention is very helpful for seq2seq models
- Explicitly copying input can be beneficial as well
- Transformers are strong models we'll come back to later

- We've now talked about most of the important core tools for NLP
- Rest of the class is more focused on applications: translation, information extraction, QA, and more, then other applications