CS395T: Structured Models for NLP
Lecture 16: RNNs II

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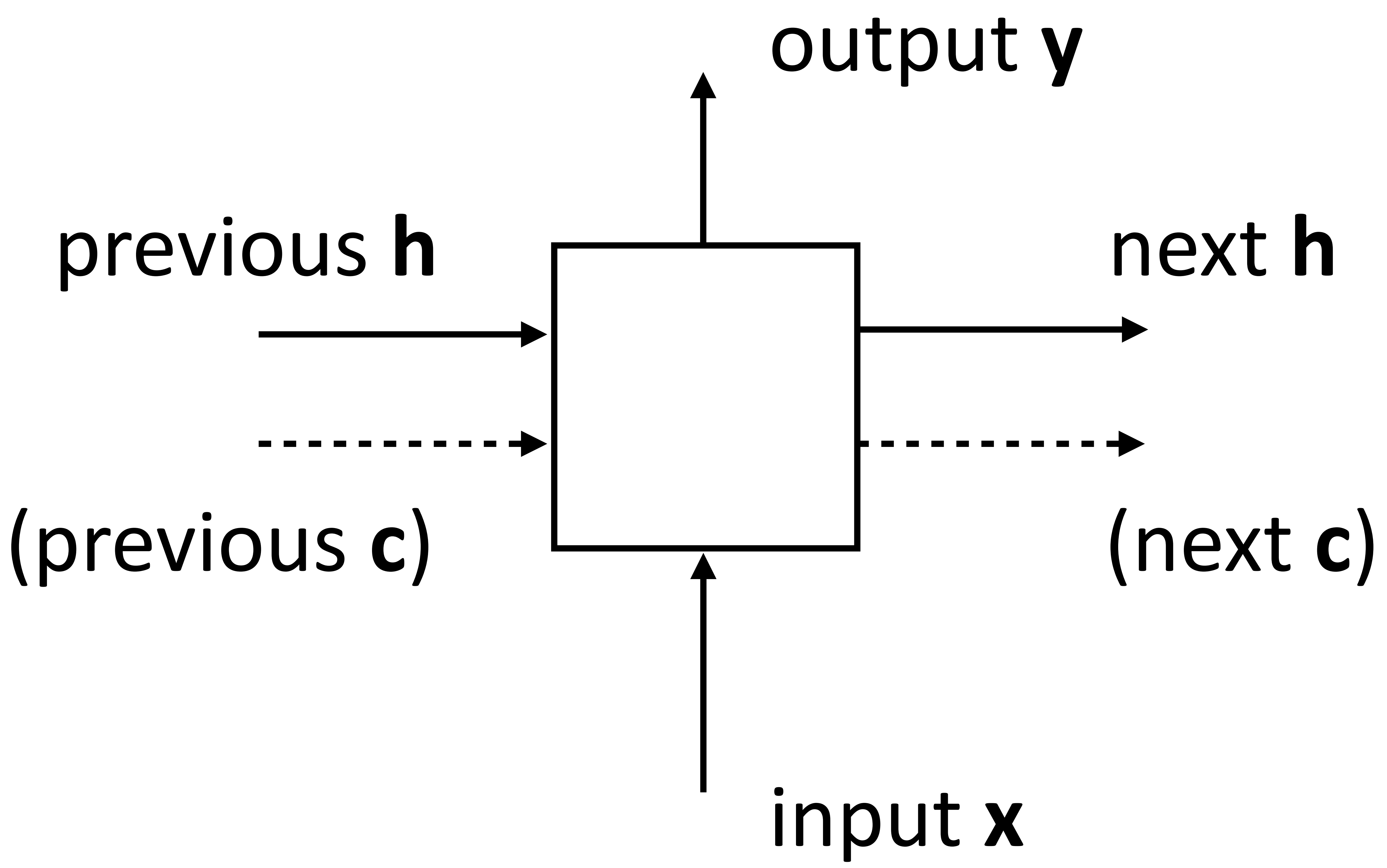
Administrivia

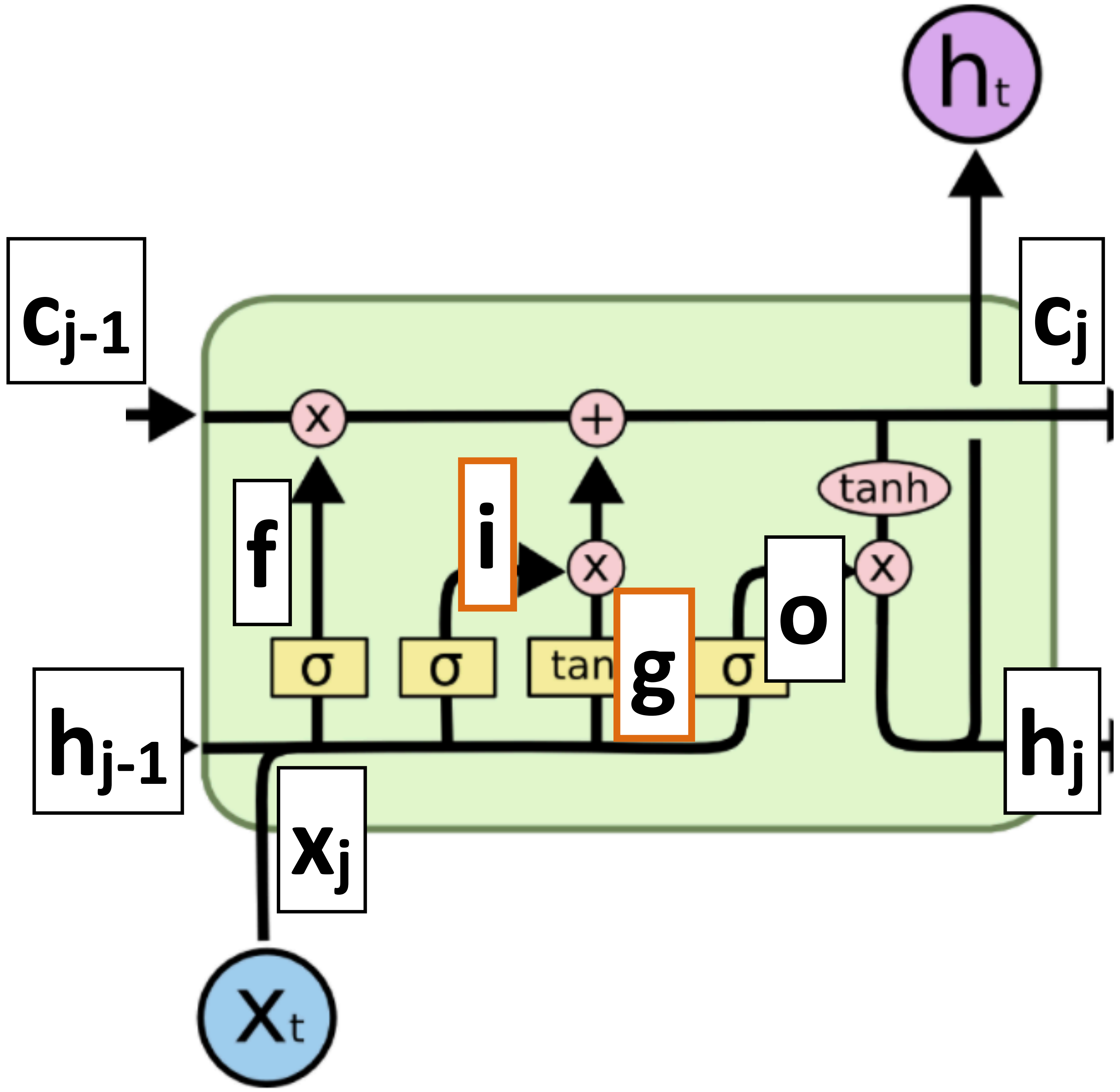
- Project 2 grades will be up tomorrow morning
- Final project guidelines posted on the website (proposals due Nov 9, presentations Dec 5+7, project due Dec 15)
  - Includes some pointers to datasets, etc.
  - Be thinking about what you want to do!

Recall: RNNs

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



Recall: LSTMs



$$\mathbf{c_j} = \mathbf{c_{j-1}} \odot \mathbf{f} + \boxed{\mathbf{g} \odot \mathbf{i}}$$

$$\mathbf{f} = \sigma(\mathbf{x_j W^{xf}} + \mathbf{h_{j-1} W^{hf}})$$

$$\boxed{\begin{aligned} \mathbf{g} &= \tanh(\mathbf{x_j W^{xg}} + \mathbf{h_{j-1} W^{hg}}) \\ \mathbf{i} &= \sigma(\mathbf{x_j W^{xi}} + \mathbf{h_{j-1} W^{hi}}) \end{aligned}}$$

$$\mathbf{h_j} = \tanh(\mathbf{c_j}) \odot \mathbf{o}$$

$$\mathbf{o} = \sigma(\mathbf{x_j W^{xo}} + \mathbf{h_{j-1} W^{ho}})$$

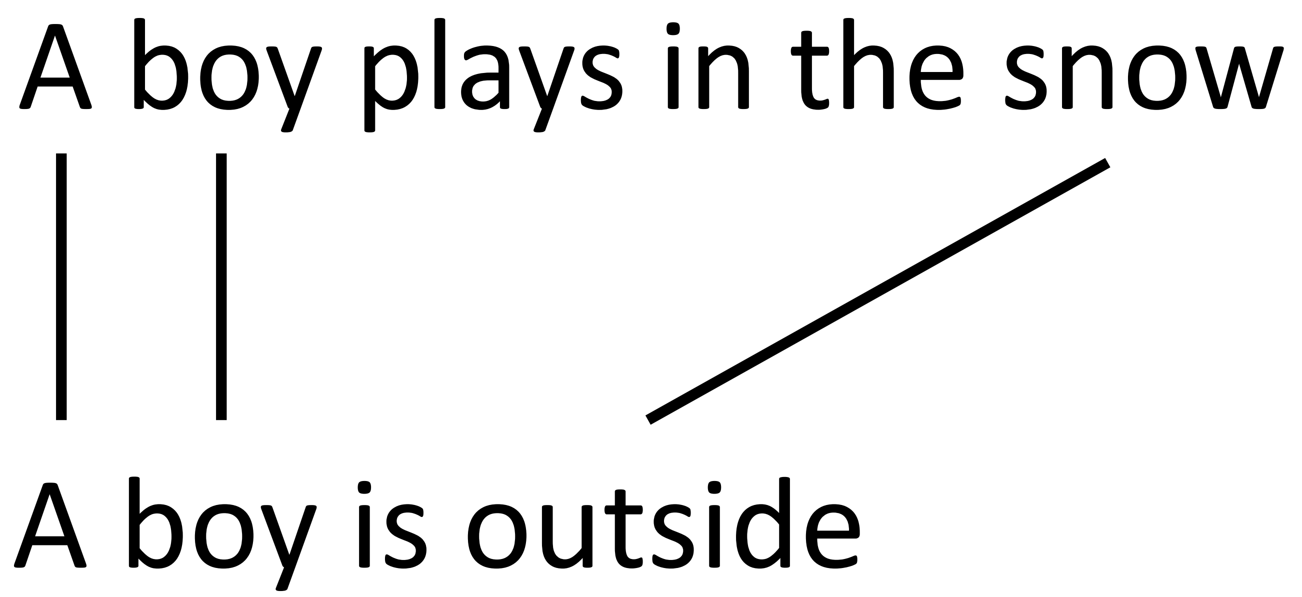
- Forget gate **f** controls how cell state changes, **i/o** control input/output
- **g** reflects the main computation of the cell

Goldberg lecture notes

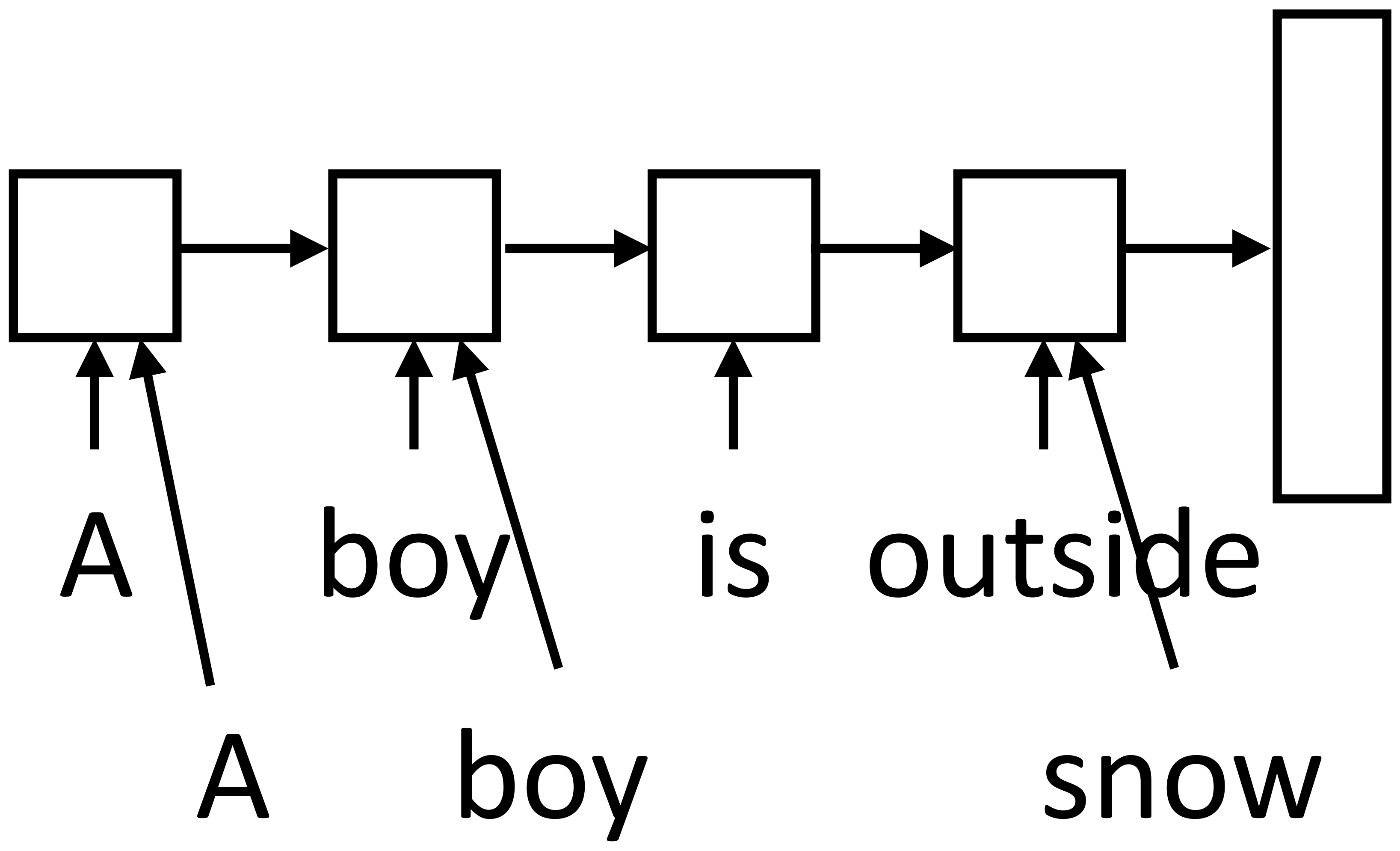
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Recall: Alignments in NLI

- Two statements often have a natural alignment between them



- Process the hypothesis with knowledge of the premise

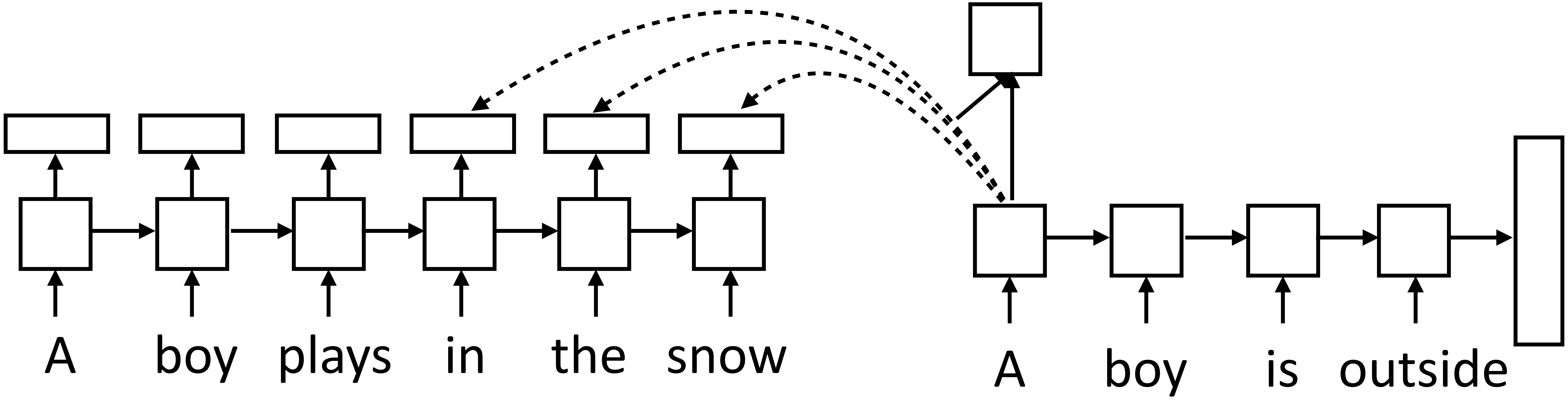


- Seeing the alignment lets you make entailment judgments as you're reading the sentence

Bowman et al. (2015)

Attention Mechanism

- *Learned* notion of alignment to some input



- Compare hidden state to encoded input vectors to compute alignment, use that to compute an input to further processing
- Attention models: 85-86% on SNLI, SOTA = 88%

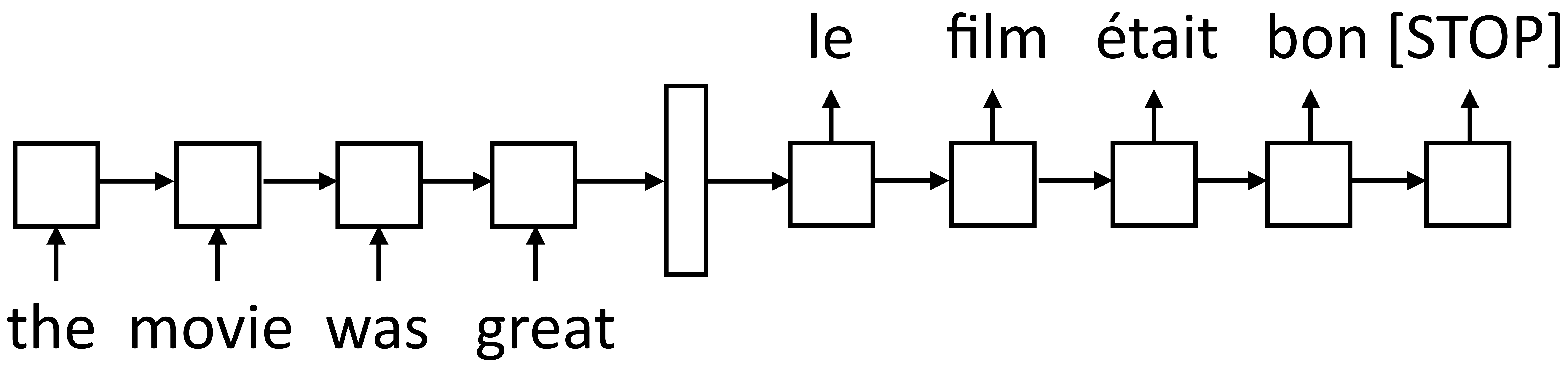
This Lecture

- Encoder-decoder models for machine translation
- Attention
- Handling rare words in machine translation
- Other applications

Encoder-Decoder Models

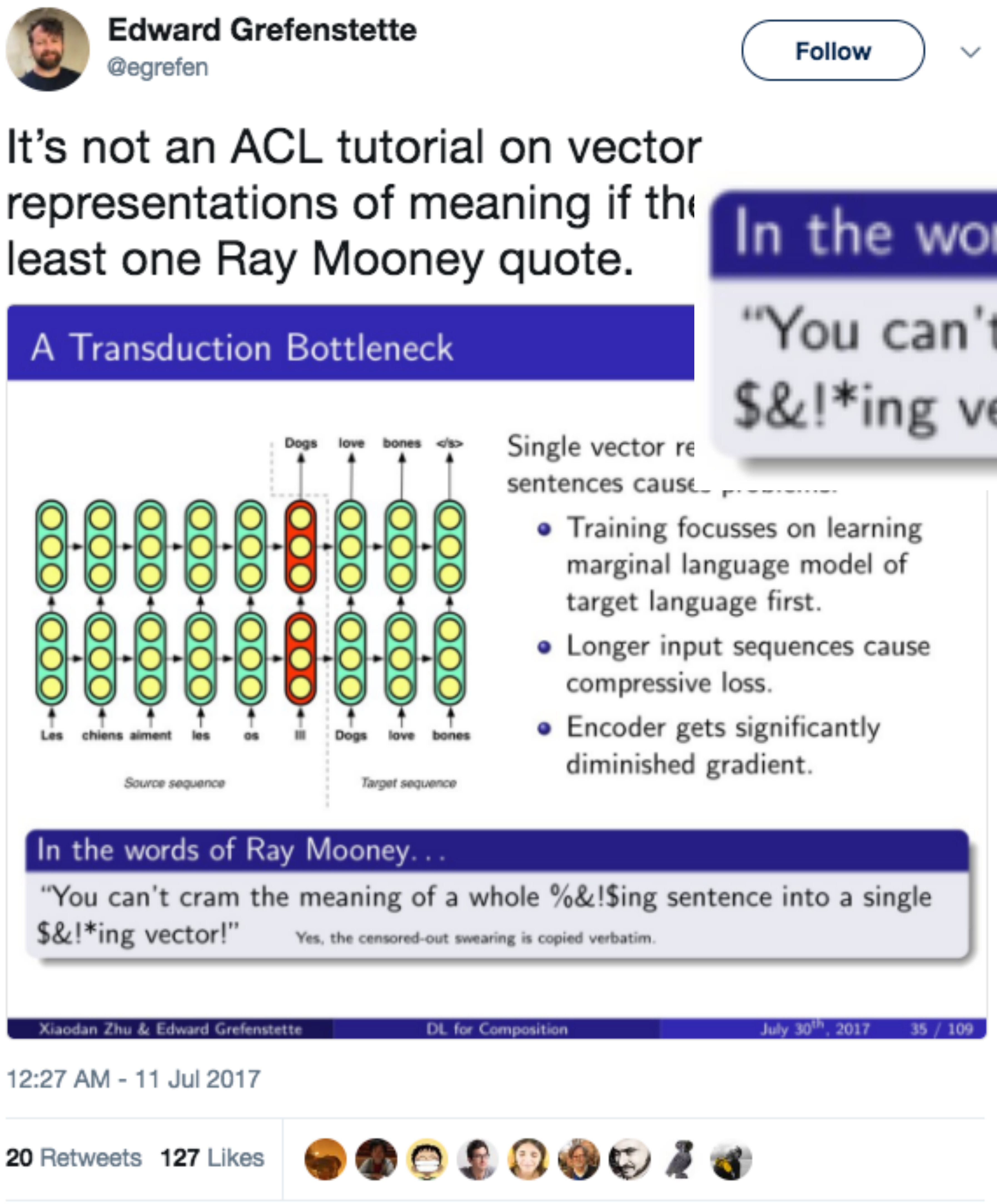
Encoder-Decoder

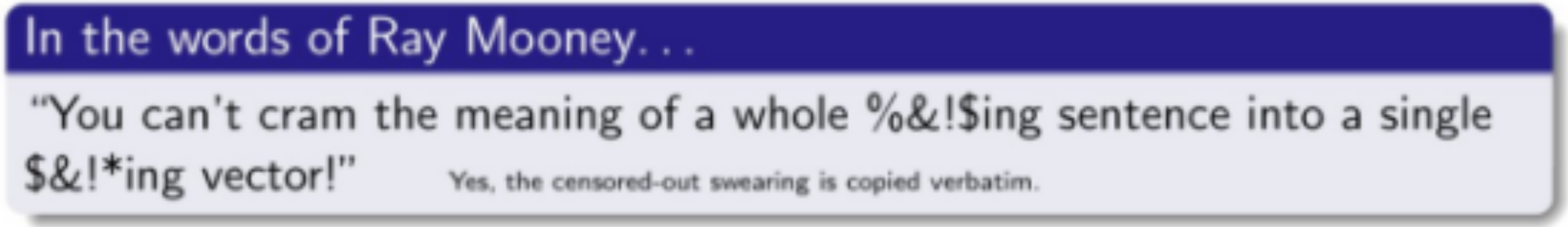
- Encode a sequence into a fixed-sized vector



- Now use that vector to produce a *sentence* as output from a separate LSTM *decoder*

Encoder-Decoder





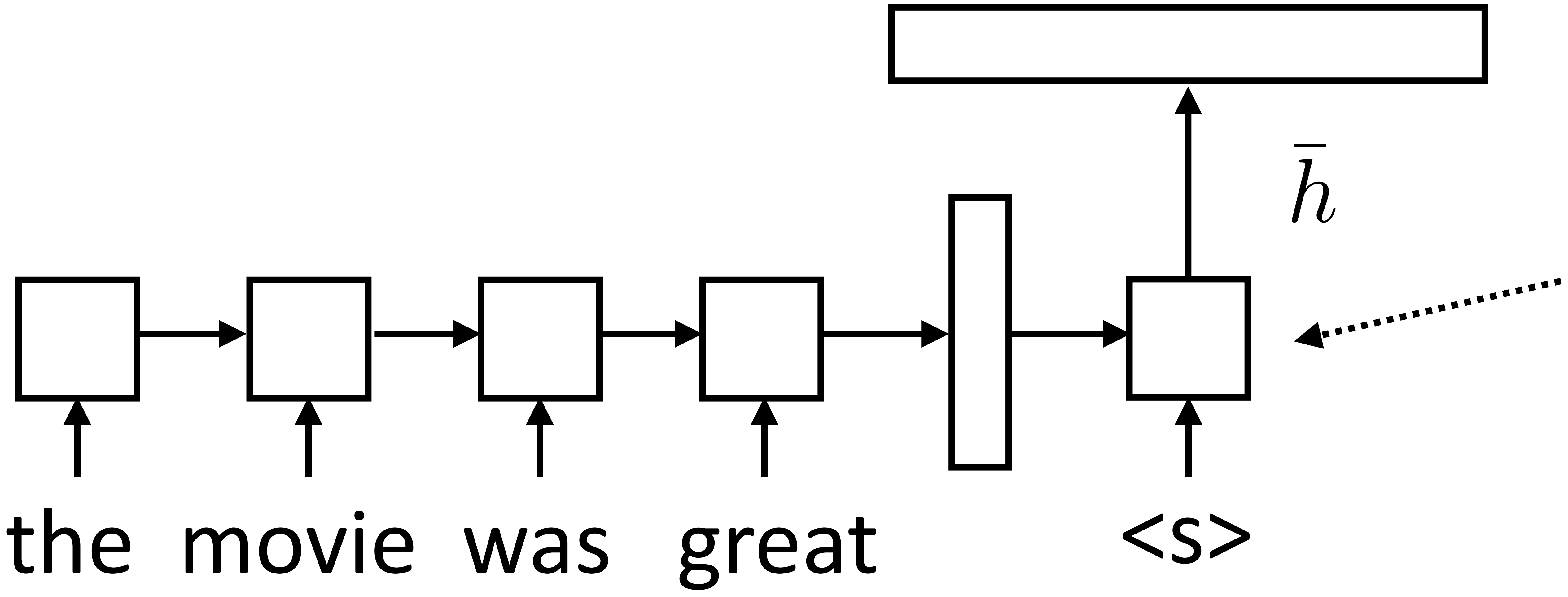
- Is this true? Sort of…we'll come back to this later

Inference

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

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

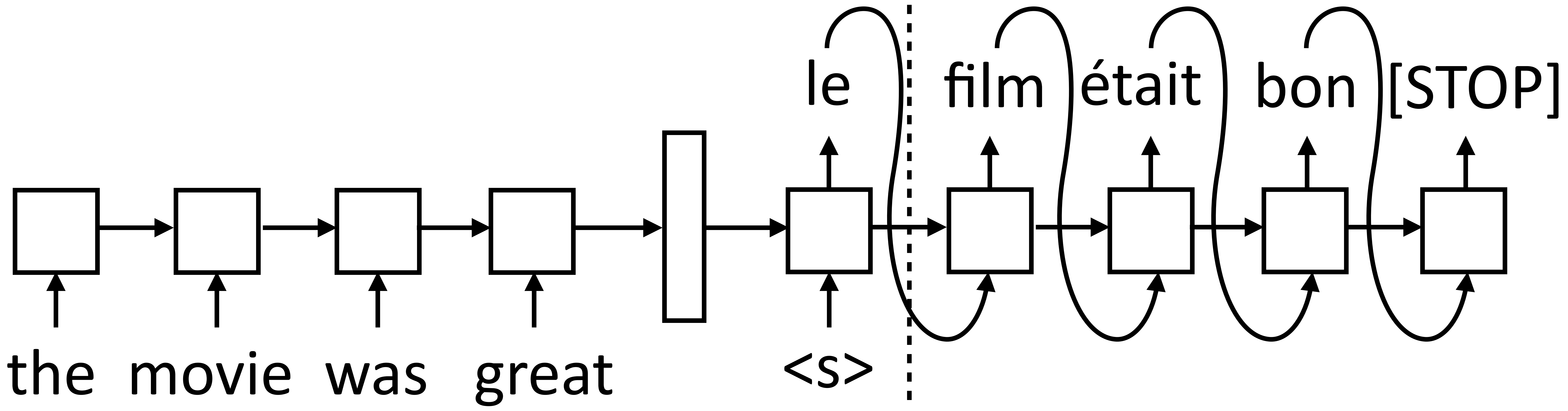
$$P(w_i|\mathbf{x}, w_{i-1}) = \text{softmax}(W\bar{h})$$



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

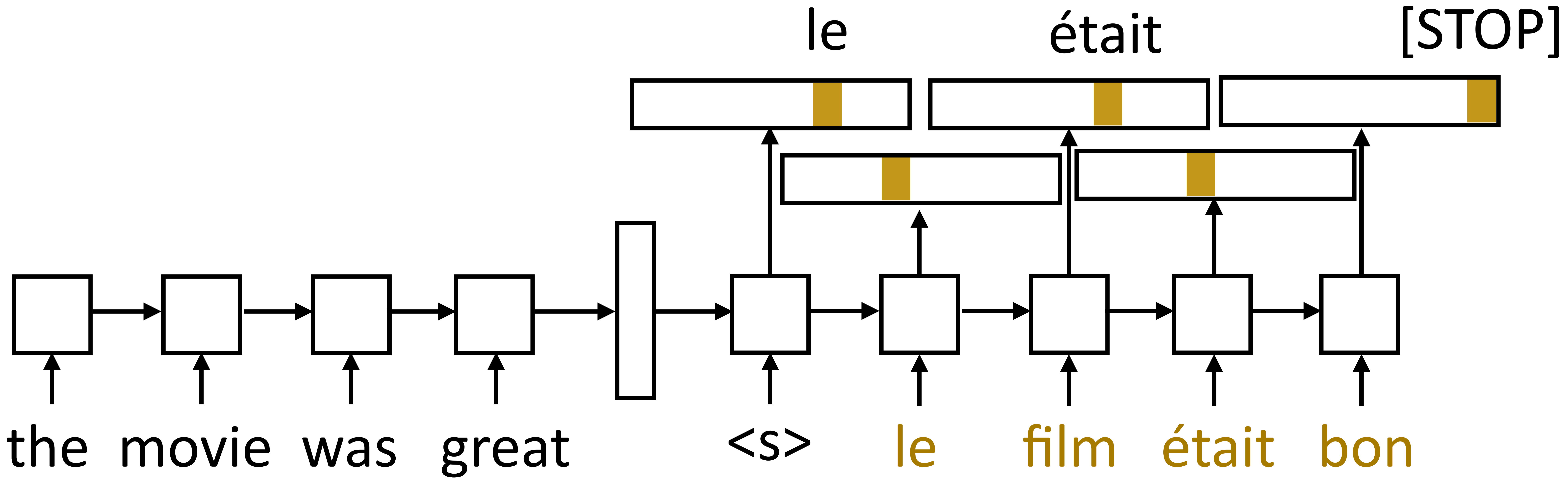
Inference

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



- 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

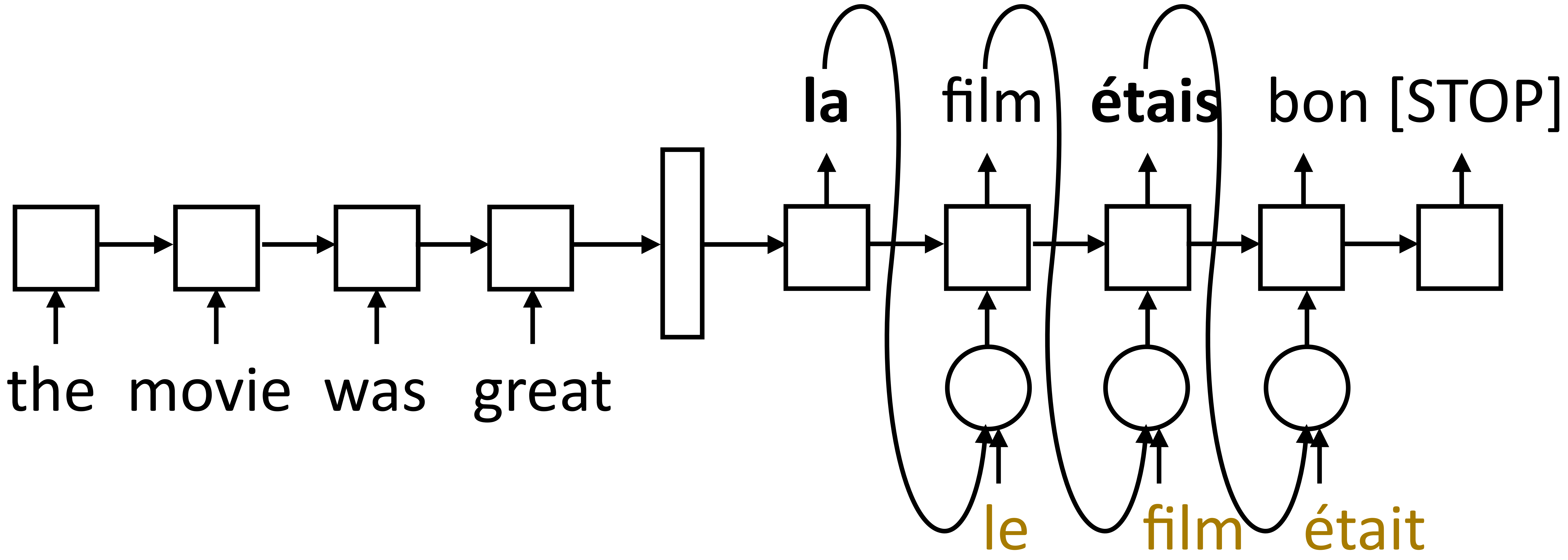
Training



- Objective: maximize $\log P(w_i^*|\mathbf{x}, w_{i-1}^*)$
- One loss term for each target-sentence word, feed the correct word regardless of model's prediction
- Length of gold sequence is known, can run the whole encoder-decoder in one computation graph and compute losses

Scheduled Sampling

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



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

Bengio et al. (2015)

Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Dynamic computation graphs framework (PyTorch, DyNet) build graphs of the correct length for a batch on-the-fly
  - Otherwise, pad everything to the right length and use a mask or indexing to access a subset of terms
- Beam search: when decoding, can use beam search rather than taking the one-best word each time
- Ensembling: these models are nonconvex, almost always works better to train several and ensemble their predictions

Machine Translation Results

WMT English-French: 12M sentence pairs, 80,000 word target vocab

Classic phrase-based system: ~33 BLEU, uses additional target-language data

Rerank with LSTMs: 36.5 BLEU (long line of work here; Devlin+ 2014)

Sutskever+ (2014) seq2seq single: 30.6 BLEU

Sutskever+ (2014) seq2seq ensemble: 34.8 BLEU

- But English-French is a really easy language pair and there's *tons* of data for it! Does this approach work for anything harder?

Machine Translation Results

WMT English-German: 4.5M sentence pairs, 50,000 word target vocab

Classic phrase-based system: 20.7 BLEU

Luong+ (2014) seq2seq: 14 BLEU

- Not nearly as good…

Attention

Problems with Neural MT 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

- Solution: include coverage in the model so we don't repeat stuff: Haitao Mi et al. (2016) for MT, See and Manning (2017) for summarization

Problems with Neural MT Models

- Unknown words:

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

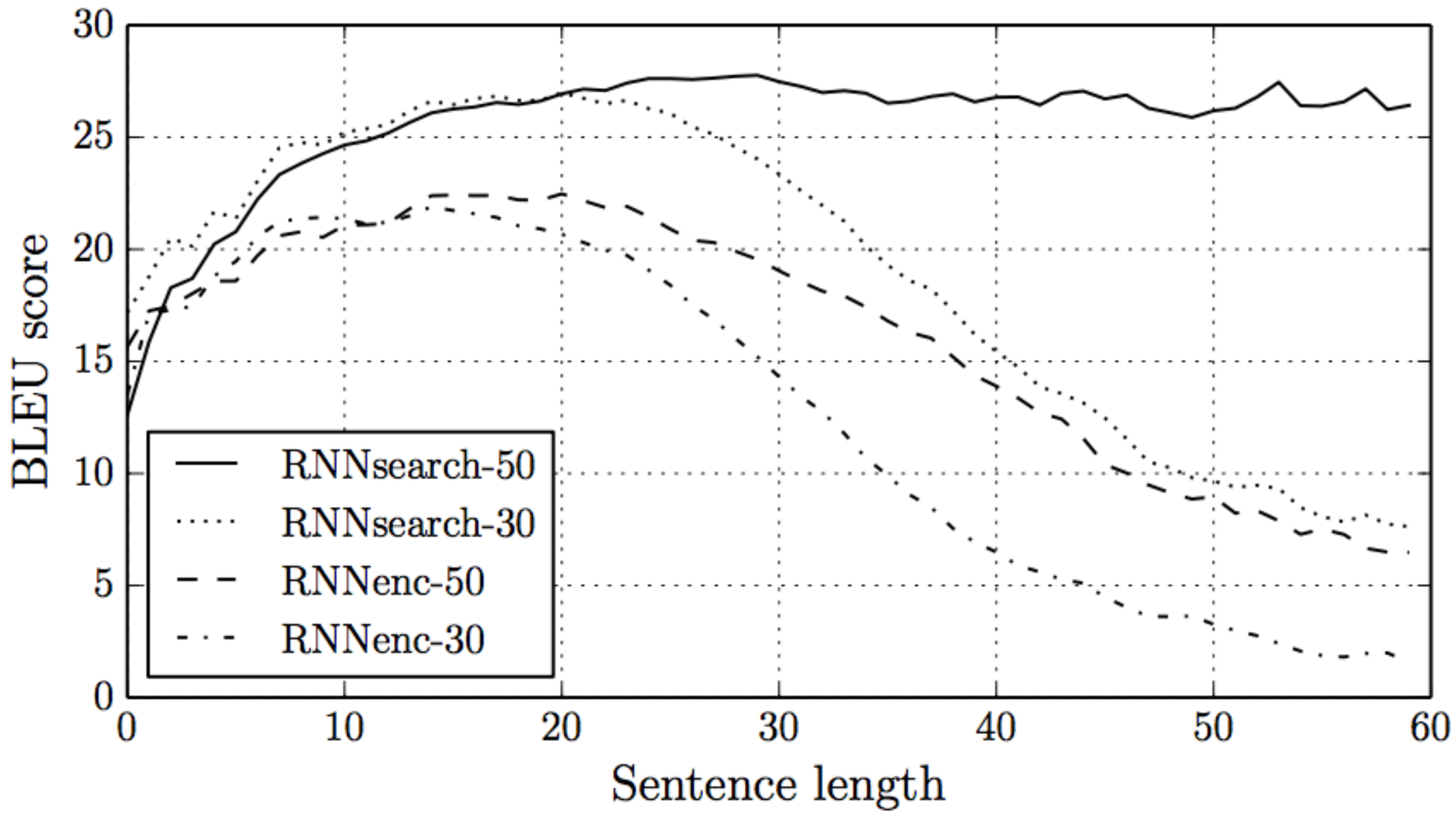
fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] . . . , a été *démonté* jeudi matin

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

- We restricted the target vocabulary to 80,000 — that throws out a lot!
- Fixed vocabulary is too restrictive, especially around named entities

Problems with Neural MT 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



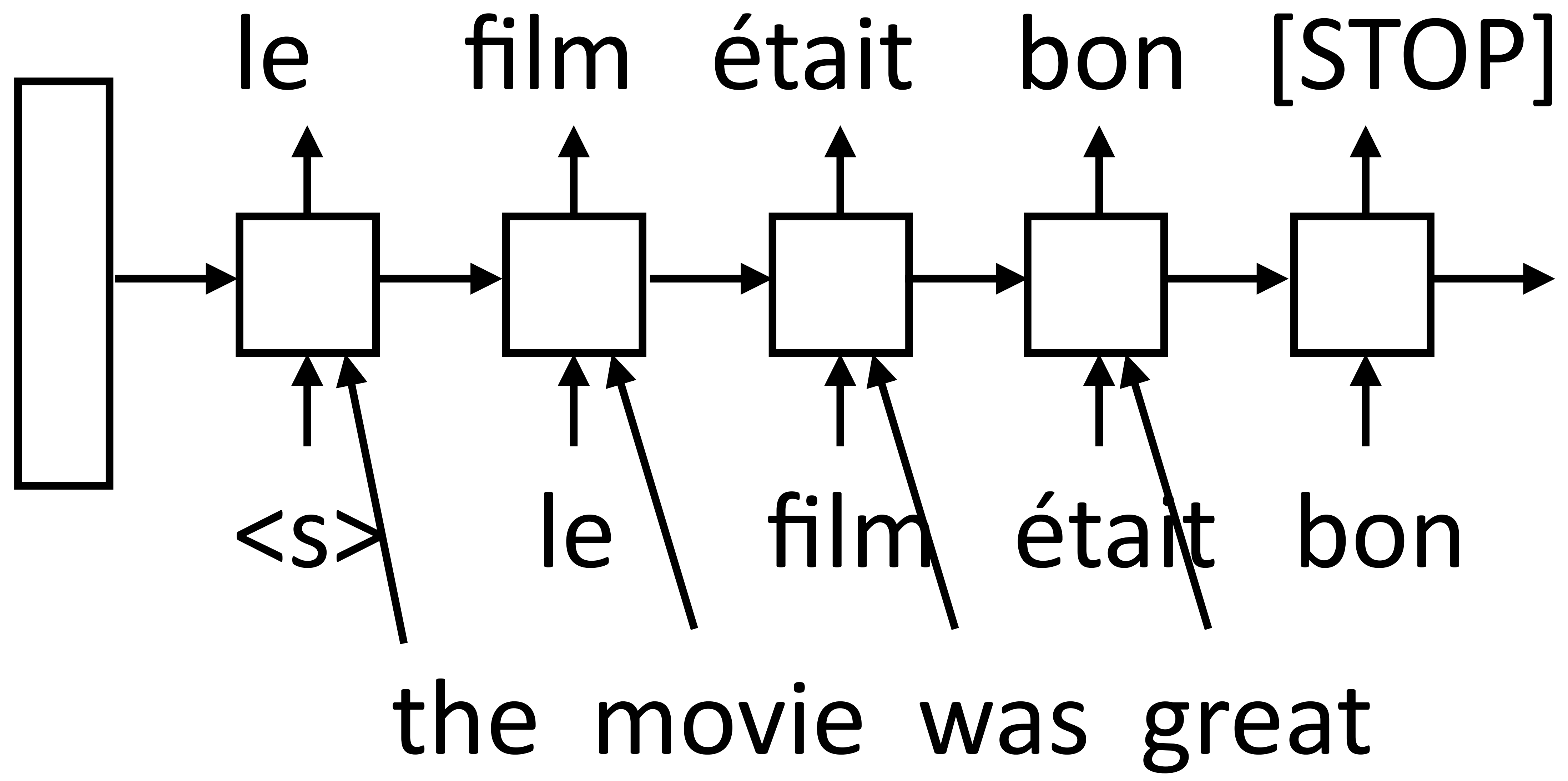
RNNsearch: introduces attention mechanism to give "variable-sized" representation

Bahdanau et al. (2014)

Aligned Inputs

- Suppose we knew the source and target would be purely monotonic

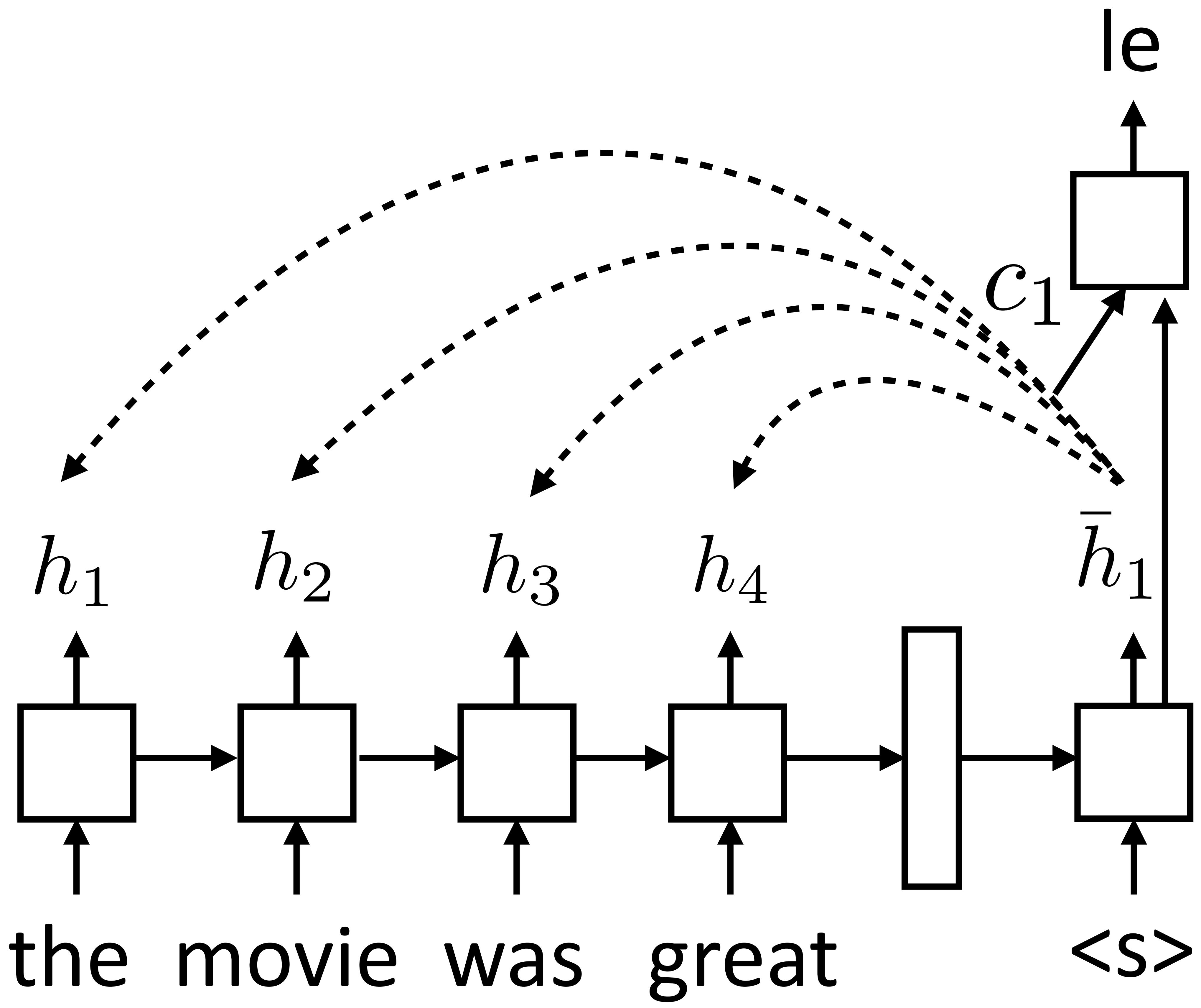
- Can look at the corresponding input word when translating — this could scale!



- Much less burden on the hidden state

Attention

- For each decoder state, compute a weighted sum of input states reflecting what's most important right now



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

- Unnormalized scalar weight

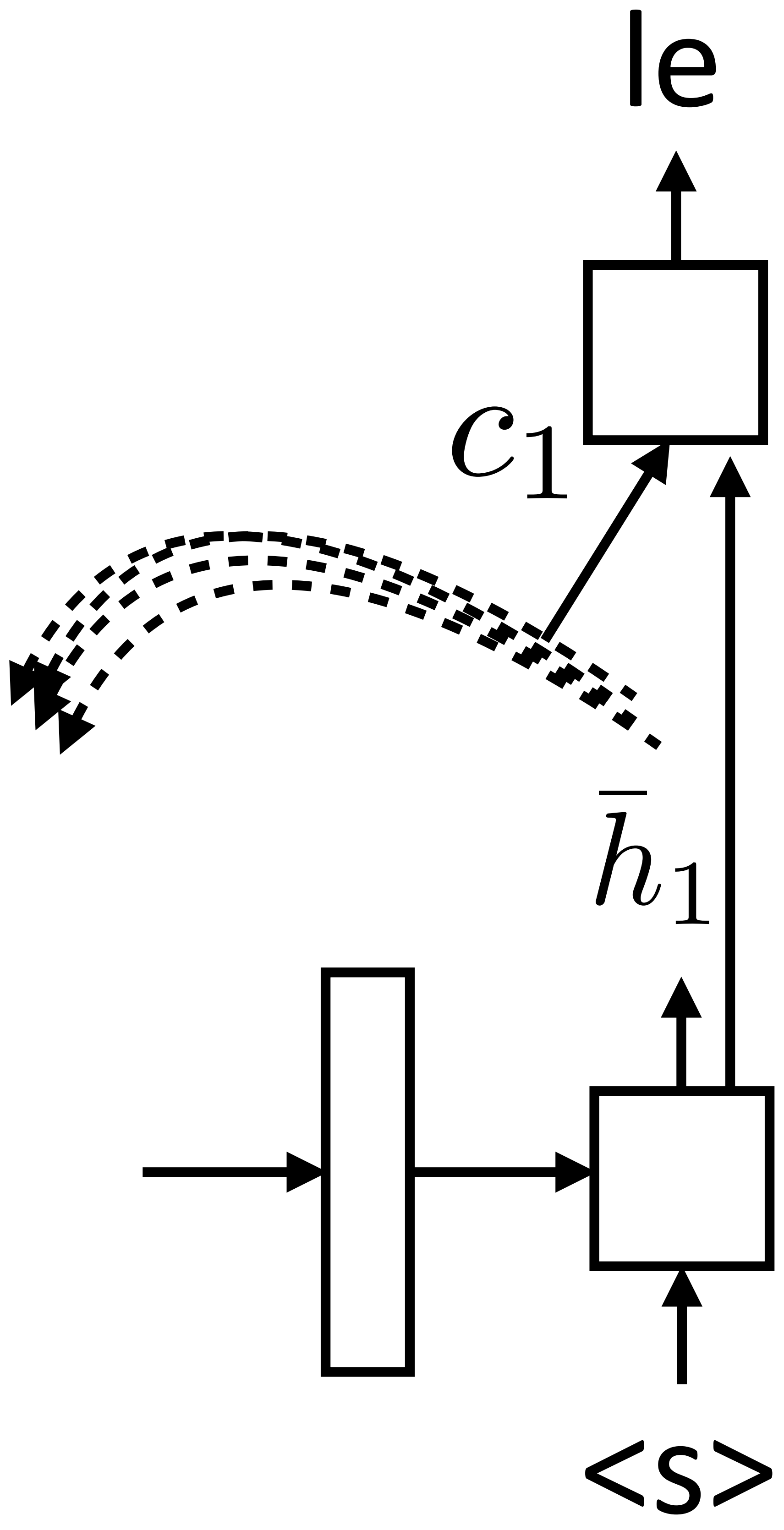
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$

- Normalized scalar weight

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

- Weighted sum of input hidden states (vector)

Attention



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

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

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

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

- Bahdanau+ (2014): additive

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

- Luong+ (2015): dot product

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

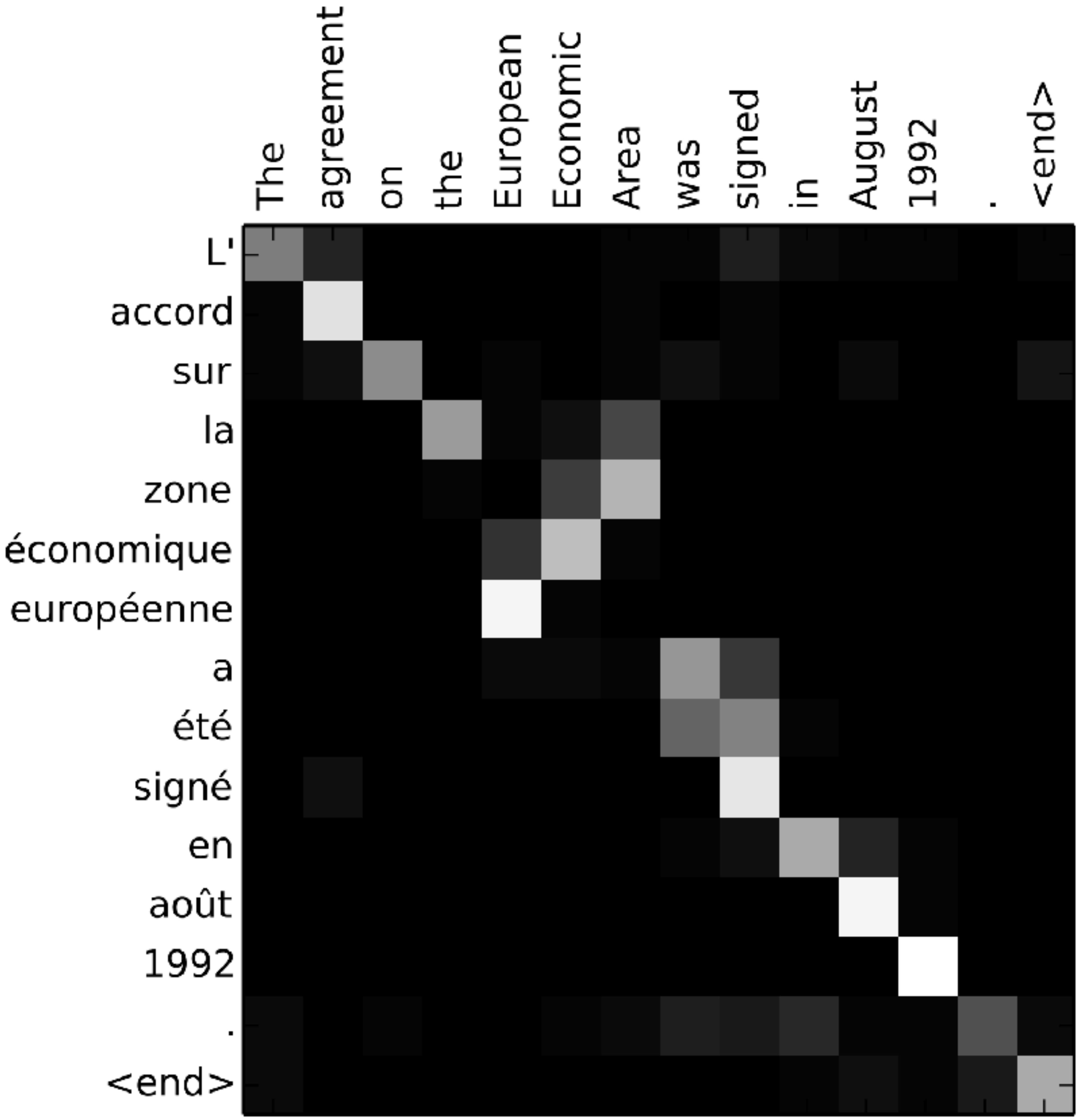
- Luong+ (2015): bilinear

- Can also use attention *weights* from previous timestep as input to current attention computation; captures monotonicity

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



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Bahdanau+ (2014) seq2seq with attention: 28.5 BLEU

- But English-French is a really easy language pair!

Results from Luong et al. (ACL 2015)

Machine Translation Results

WMT English-German: 4.5M sentence pairs, 50,000 word target vocab

Classic phrase-based system: 20.7 BLEU

Basic seq2seq: 14 BLEU

seq2seq with attention: 16.8 BLEU

seq2seq with attention aware of previous attention: 18.1 BLEU

^ ensemble + rare word handling: 23.0 BLEU

- Attention more critical for the harder English-German task

Results from Luong et al. (EMNLP 2015)

Dealing with Rare Words

Unknown Words

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

$\boxed{2}$ $\boxed{1}$ $\boxed{2}$

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

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

1) Named entities: copy (and maybe transliterate)

2) Rare concepts: may be able to get from transliteration, generally hard

- Neural MT models have to generate from a fixed vocabulary, but we at least want to be able to copy named entities

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

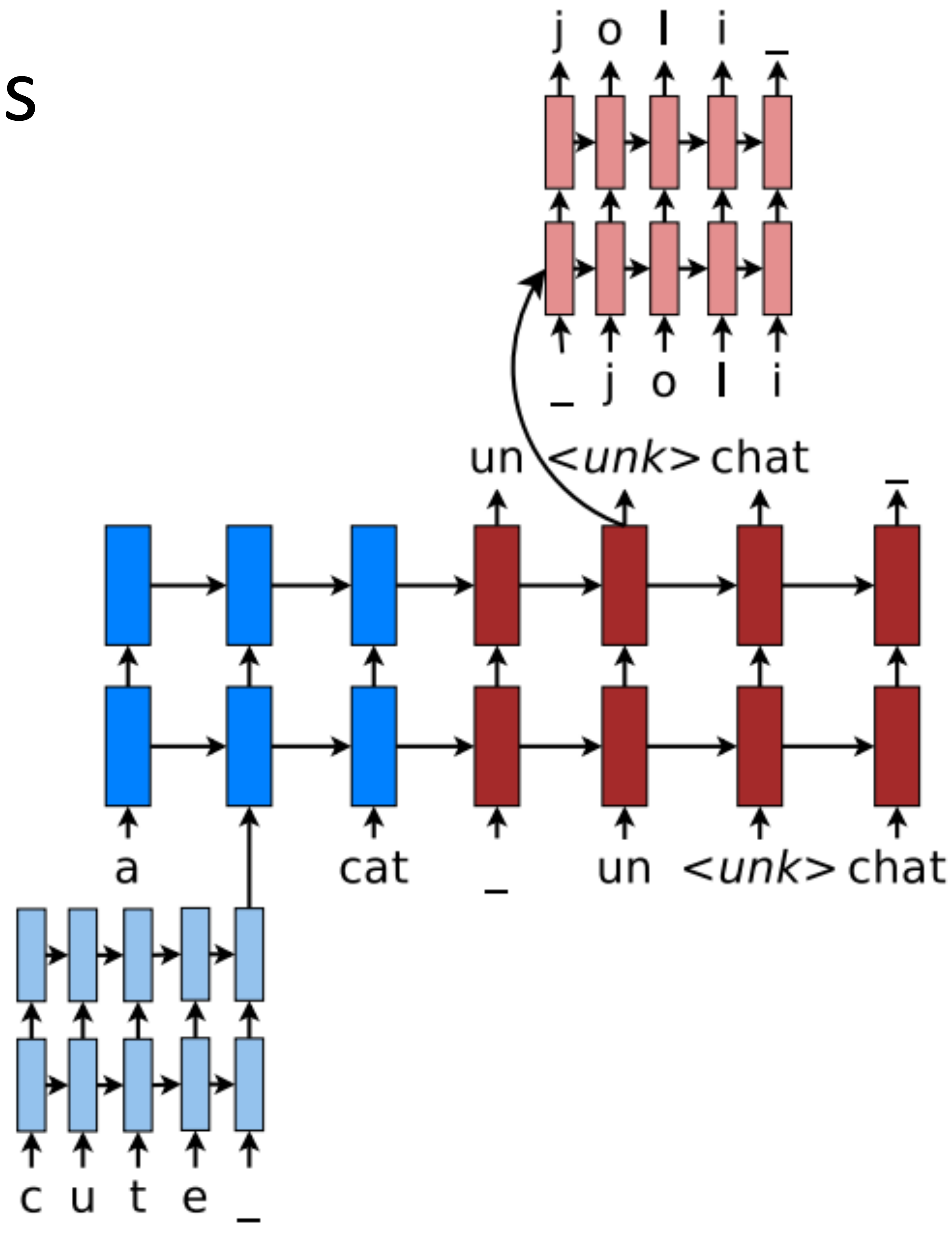
Copying

- Predict an unk token with a pointer to a source word to copy
- Input   en: The $\underline{unk}_1$ portico in $\underline{unk}_2$ . . .
- Output   fr: Le $\underline{unk}_\emptyset$ $\underline{unk}_1$ de $\underline{unk}_2$ . . .
- Easy to do and helps a lot! (+ a few BLEU points, typically)
- Similar to pointer networks, which we'll see later

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

Rare Words: Character Models

- If we predict an unk token, generate the results from a character LSTM
- Can potentially transliterate new concepts, but architecture is more complicated and slower to train
- Models like this in part contributed to dynamic computation graph frameworks becoming popular



Luong et al. (2016)

Rare Words: Word Piece Models

- Use Huffman encoding on a corpus, keep most common *k* (~10,000) character sequences for source and target

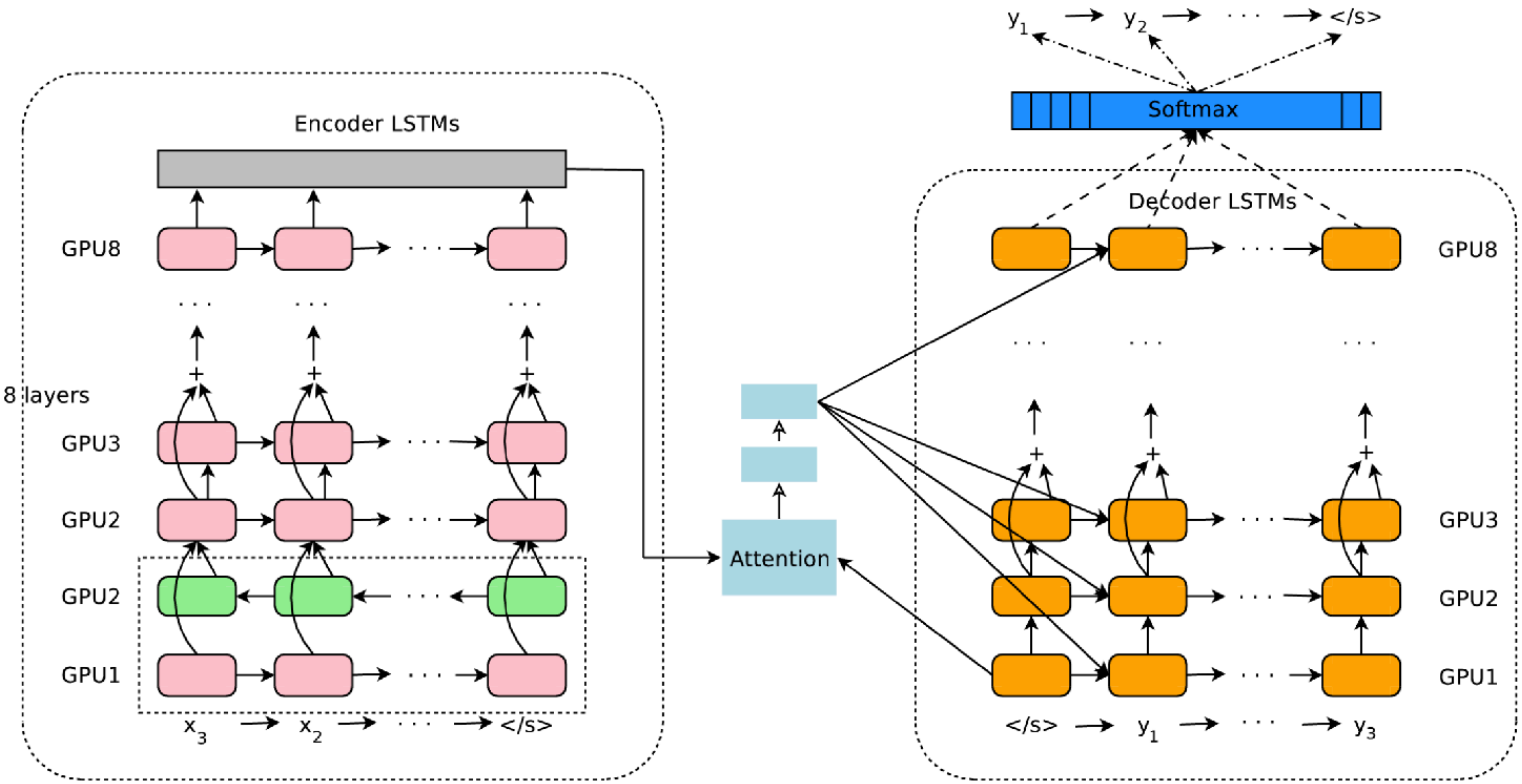
Input: _the **_eco tax** _port i co _in _Po nt - de - Bu is ...

Output: _le _port ique **_éco taxe** _de _Pont - de - Bui s

- Captures common words and parts of rare words
- Subword structure may make it easier to translate
- Model balances translating and transliterating without explicit switching

Wu et al. (2016)

Google's NMT System



- 8-layer LSTM encoder-decoder with attention, word piece vocabulary of 8k-32k

Wu et al. (2016)

Google's NMT System

English-French:

Google's phrase-based system: 37.0 BLEU

Luong+ (2015) seq2seq ensemble with rare word handling: 37.5 BLEU

Google's 32k word pieces: 38.95 BLEU

English-German:

Google's phrase-based system: 20.7 BLEU

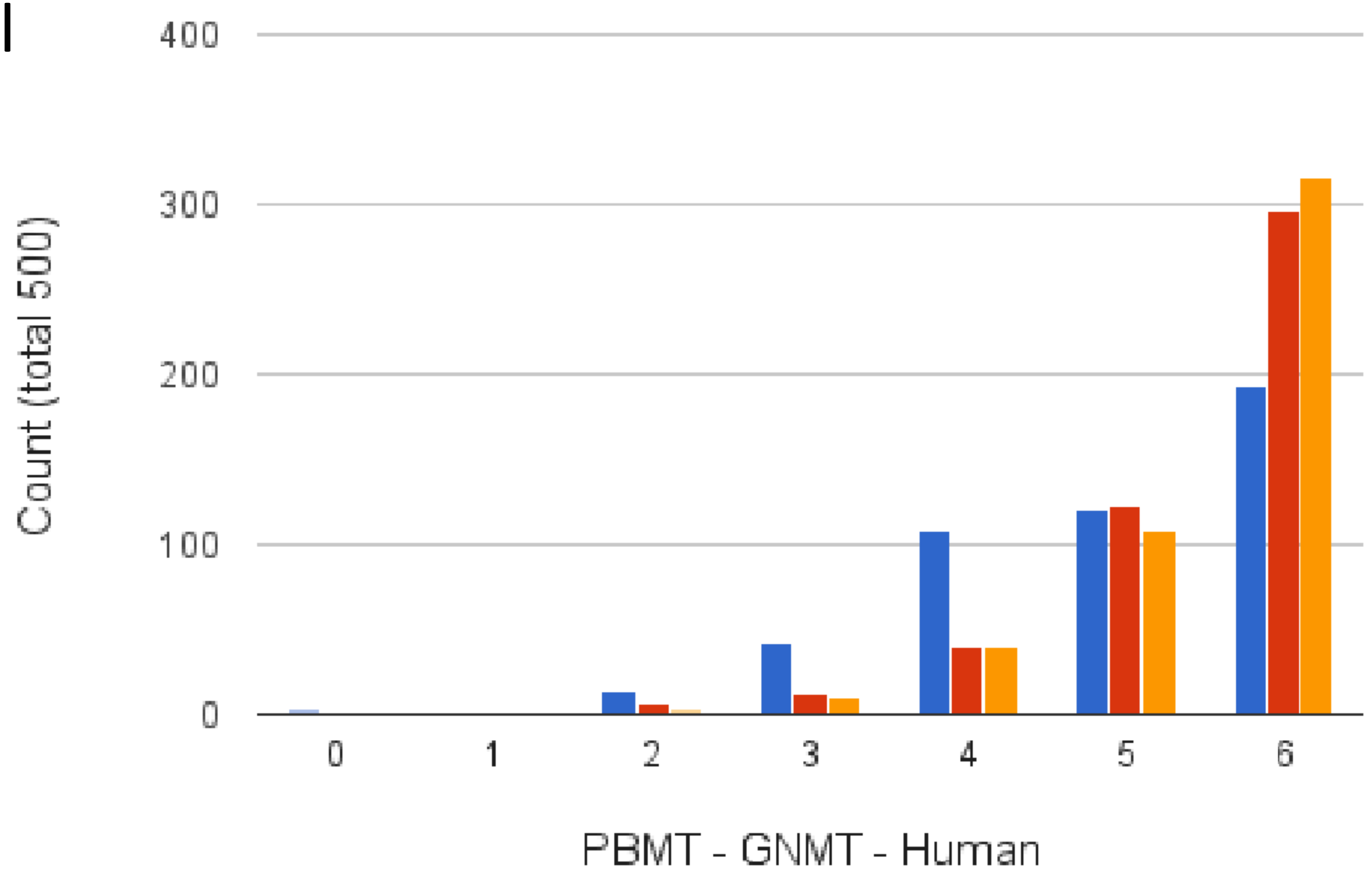
Luong+ (2015) seq2seq ensemble with rare word handling: 23.0 BLEU

Google's 32k word pieces: 24.2 BLEU

Wu et al. (2016)

Human Evaluation (En-Es)

- Similar to human-level performance *on English-Spanish*

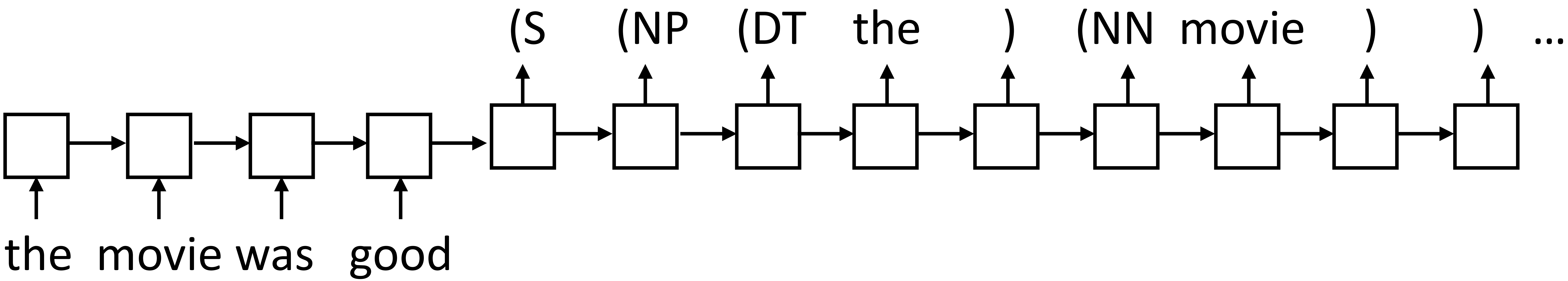


Wu et al. (2016)

Other Applications

Other Applications

- Parsing: input is a sentence, output is a bracketed sentence

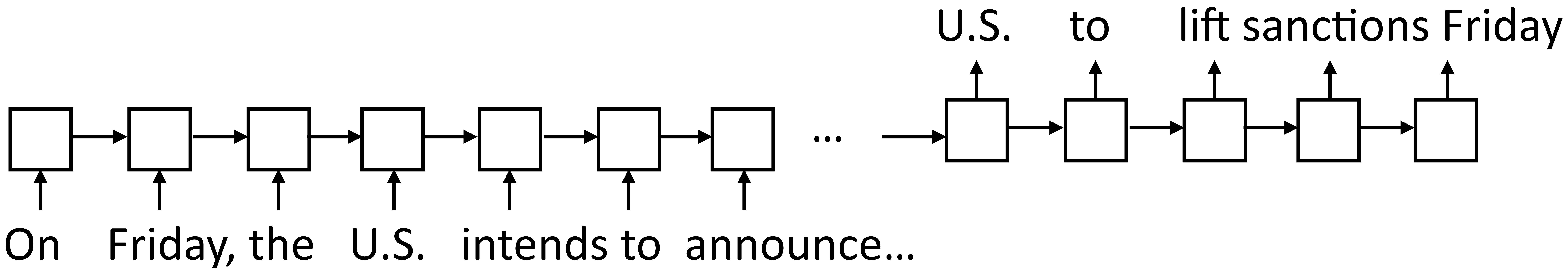


- Attention is essential: <70 F1 without it, 88.3 F1 / 90.5 F1 (ensemble) with it
- The best parsers still use some structure — we'll come back to these

Vinyals et al. (2014)

Other Applications

- Summarization/compression
  - Input: article/sentence, output: compressed article/sentence



- Long articles, hard to deal with even with attention
- Speech recognition/text-to-speech: neural nets are good at dealing with continuous speech signals!

Takeaways

- RNNs are effective at machine translation, but lots of tricks to get them to work right
- Attention is a critical way to get a better representation of the input
- Handling rare words is important, lots of techniques here
- Encoder-decoder models can be successfully applied to most tasks where you generate language as output