Seq2Seq + Attention/Copy

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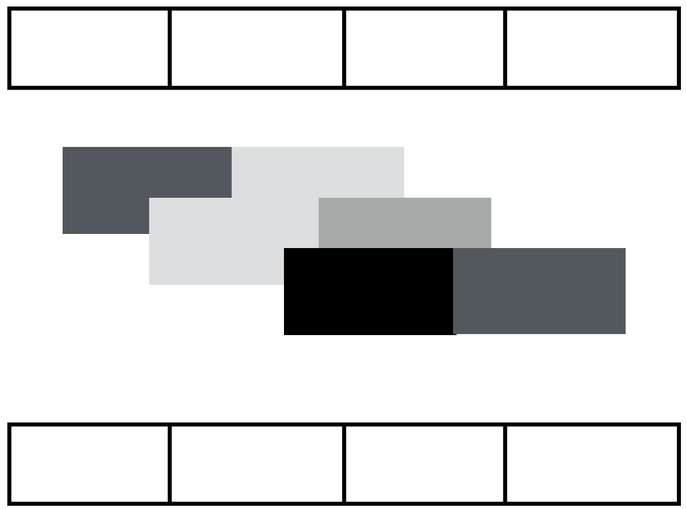
(many slides from Greg Durrett)

This Week

- Sequence-to-Sequence Model
- Attention Mechanism
- Copy Mechanism
- Transformer Architecture

Recall: CNNs vs. LSTMs

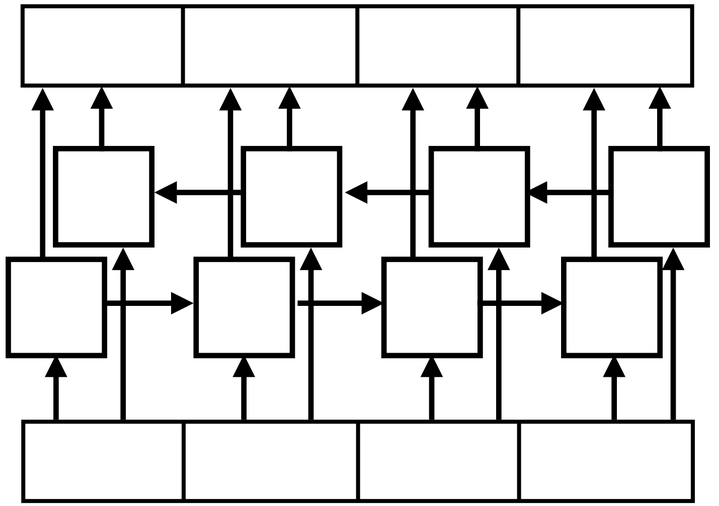


O(n) x c

c filters,
m x k each

n x k

the movie was good



n x 2c

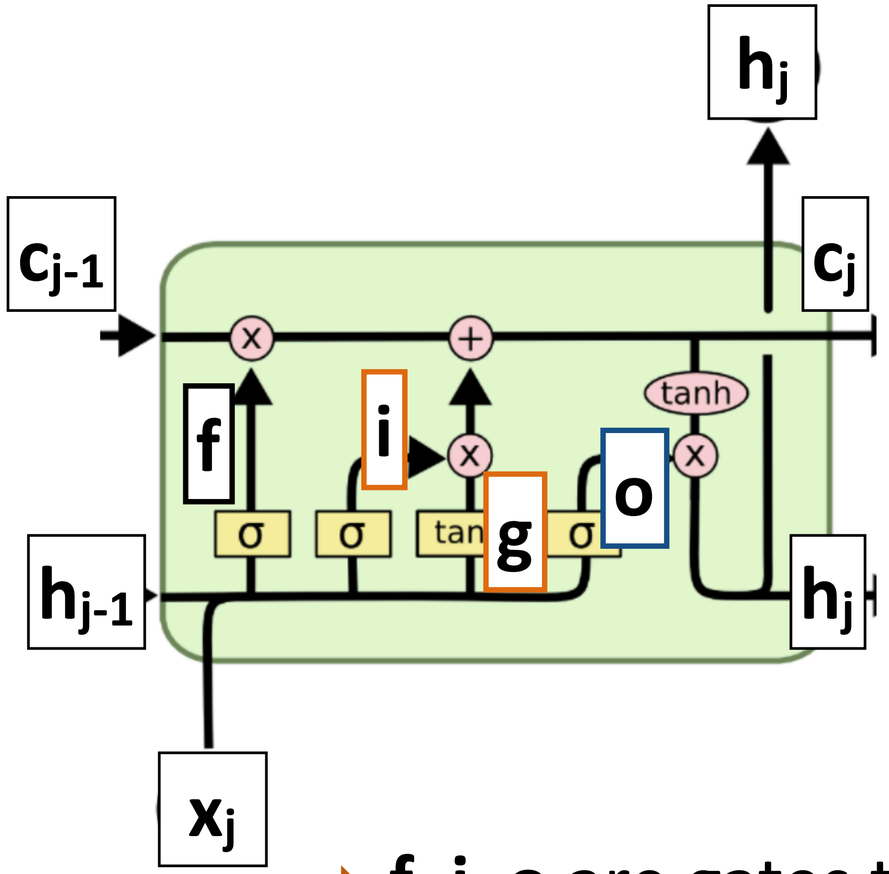
BiLSTM with
hidden size c

n x k

the movie was good

- 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

LSTMs



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

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

$$\mathbf{g} = \tanh(\mathbf{x_j W^{xg}} + \mathbf{h_{j-1} W^{hg}})$$

$$\mathbf{i} = \sigma(\mathbf{x_j W^{xi}} + \mathbf{h_{j-1} W^{hi}})$$

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

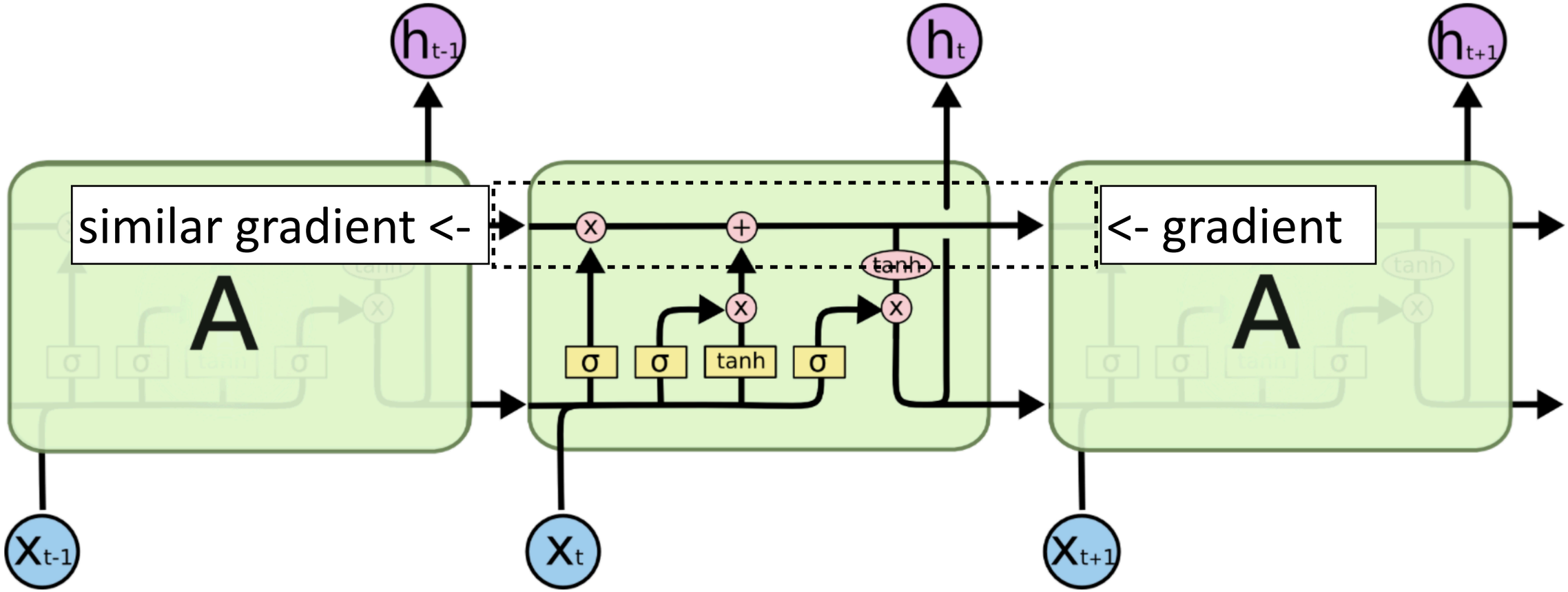
$$\mathbf{o} = \sigma(\mathbf{x_j W^{xo}} + \mathbf{h_{j-1} W^{ho}})$$

- **f**, **i**, **o** are gates that control information flow
- **g** reflects the main computation of the cell

Hochreiter & Schmidhuber (1997)

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

LSTMs

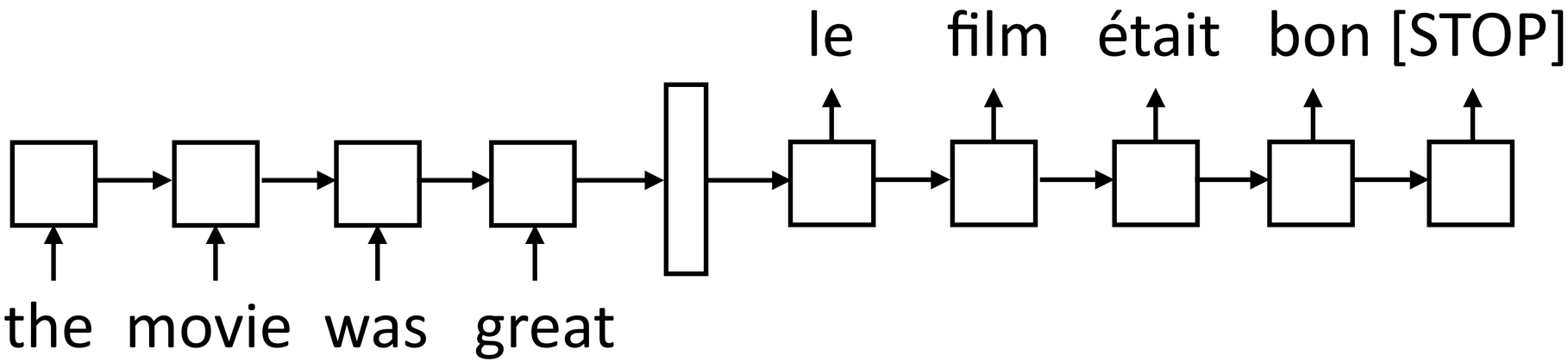


- Gradient still diminishes, but in a controlled way and generally by less — usually initialize forget gate = 1 to remember everything to start

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

Encoder-Decoder

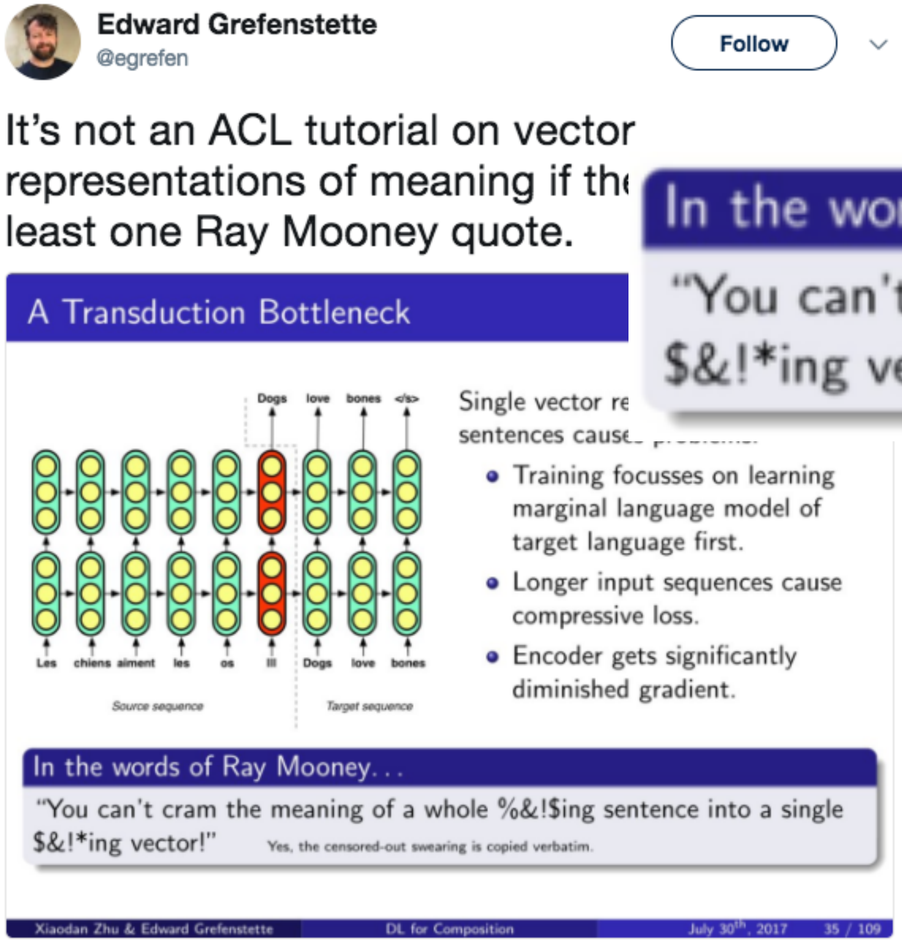
- Encode a sequence into a fixed-sized vector



- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*
- Machine translation, NLG, summarization, dialog, and many other tasks (e.g., semantic parsing, syntactic parsing) can be done using this framework.

Sutskever et al. (2014)

Encoder-Decoder

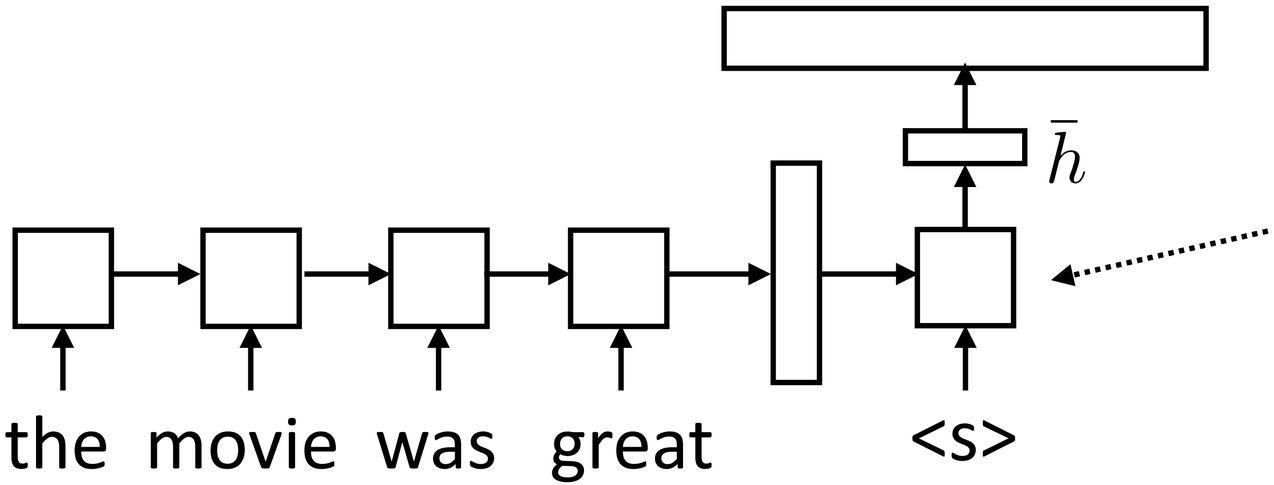


In the words of Ray Mooney. . .
"You can't cram the meaning of a whole %&!$ing sentence into a single $&!*ing vector!"
Yes, the censored-out swearing is copied verbatim.

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



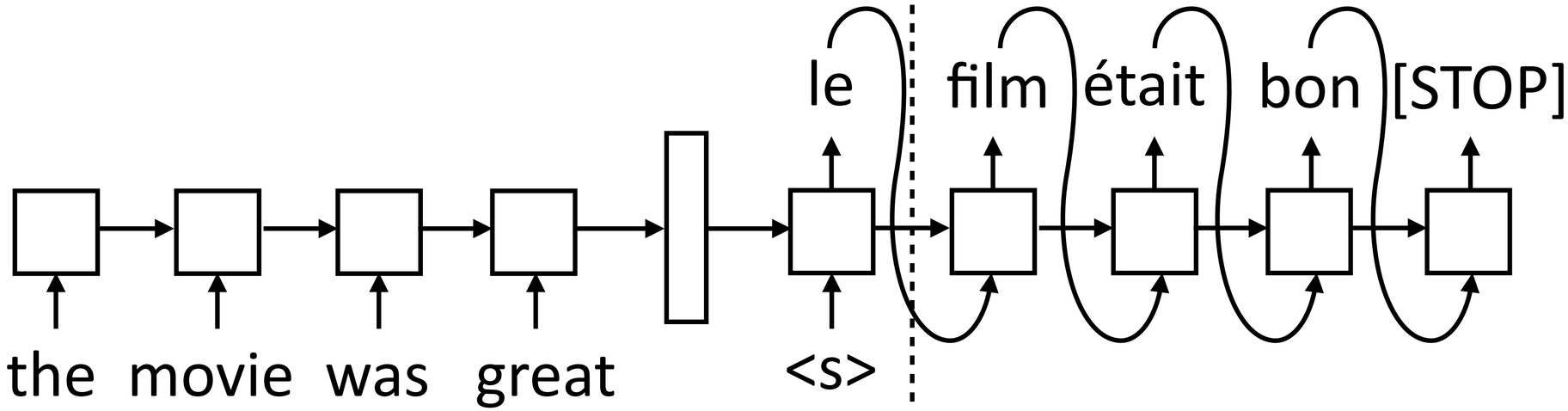
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h})$$

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

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

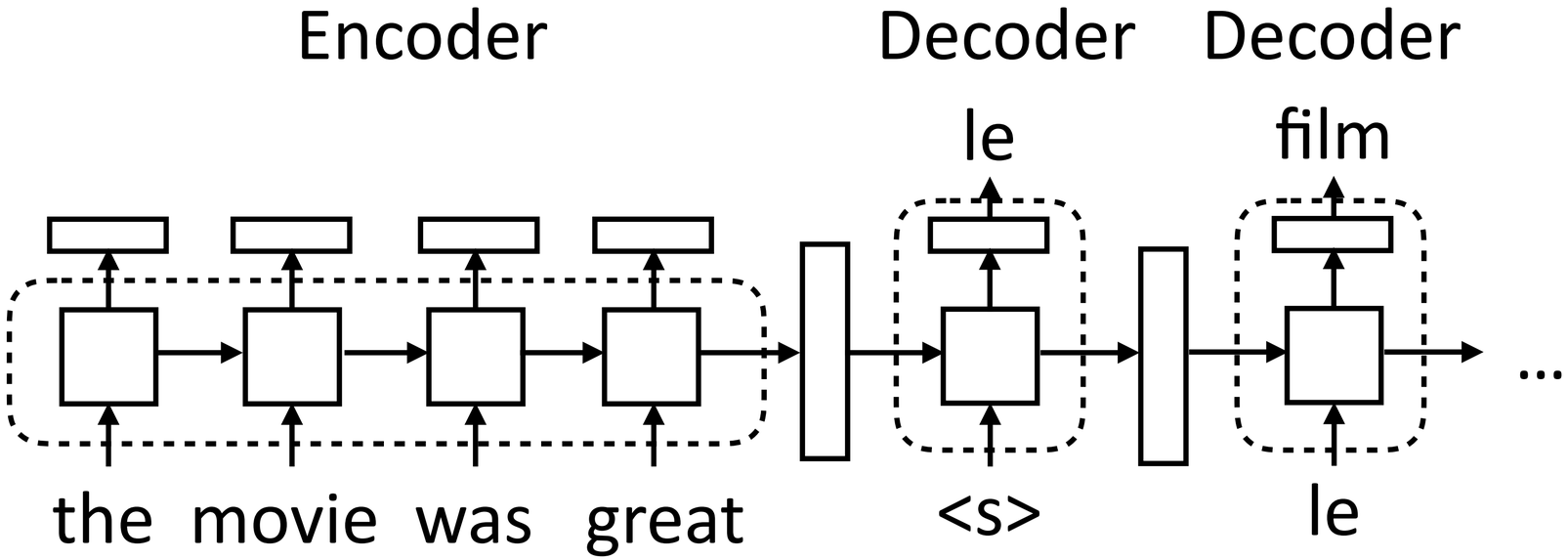
Inference

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



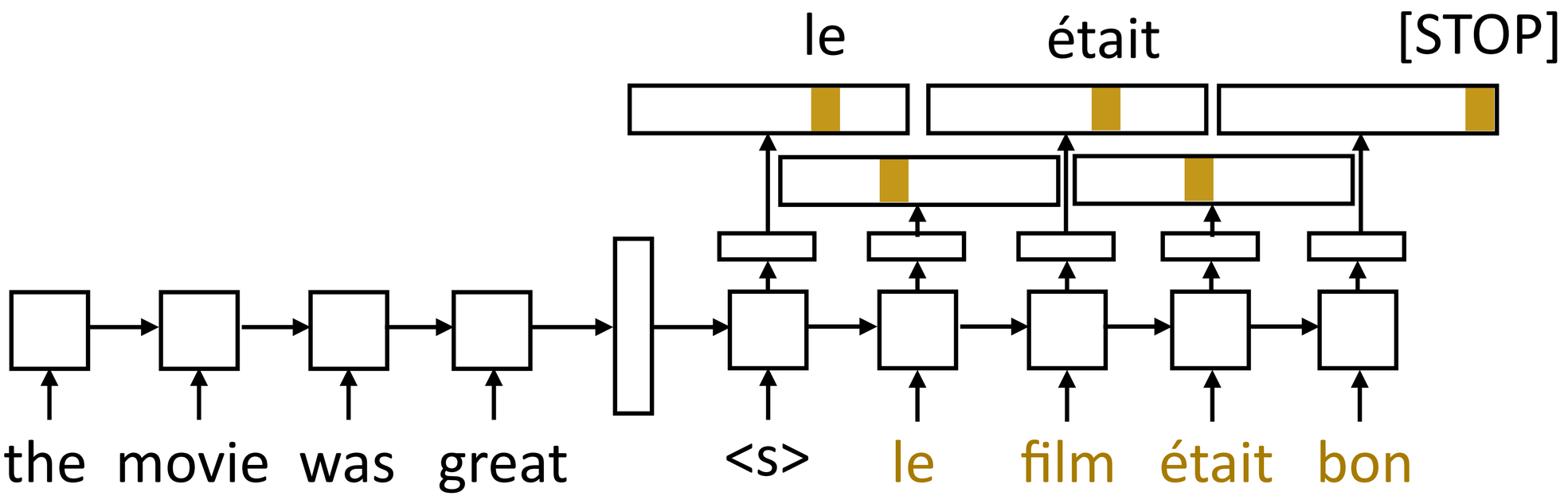
- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

Implementing seq2seq Models



- 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

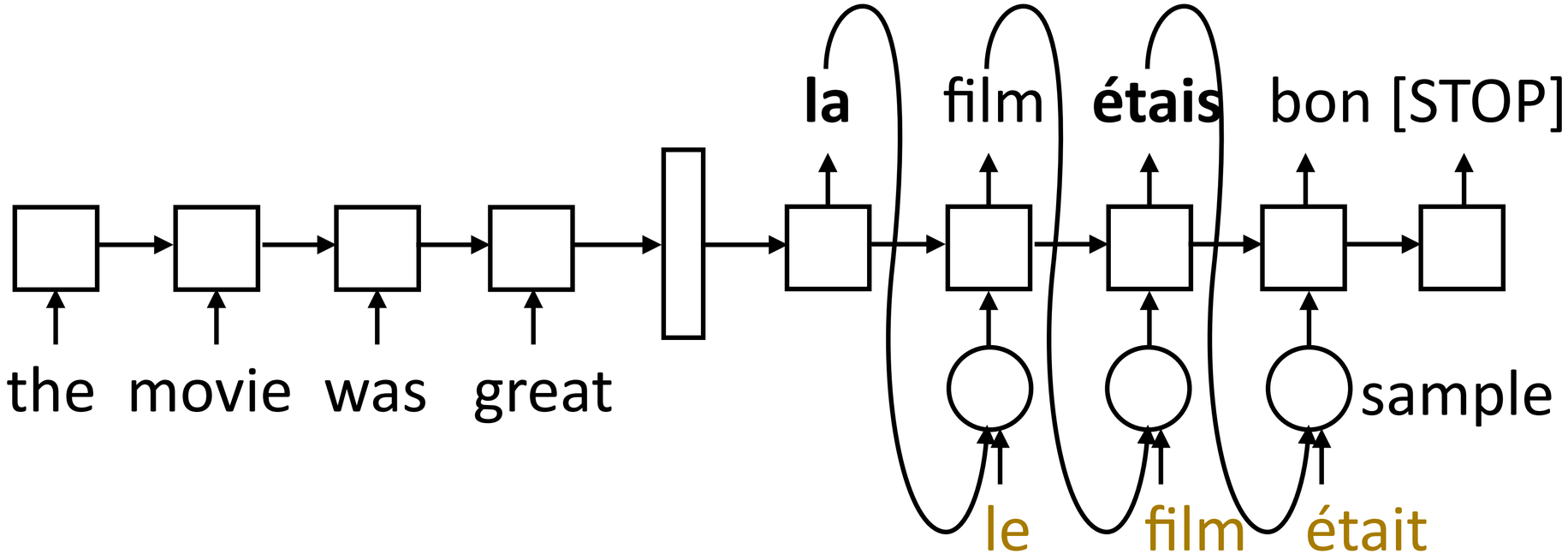


- Objective: maximize $$\sum_{(\mathbf{x},\mathbf{y})} \sum_{i=1}^{n} \log P(y_i^* | \mathbf{x}, y_1^*, \ldots, y_{i-1}^*)$$

- 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



- 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)

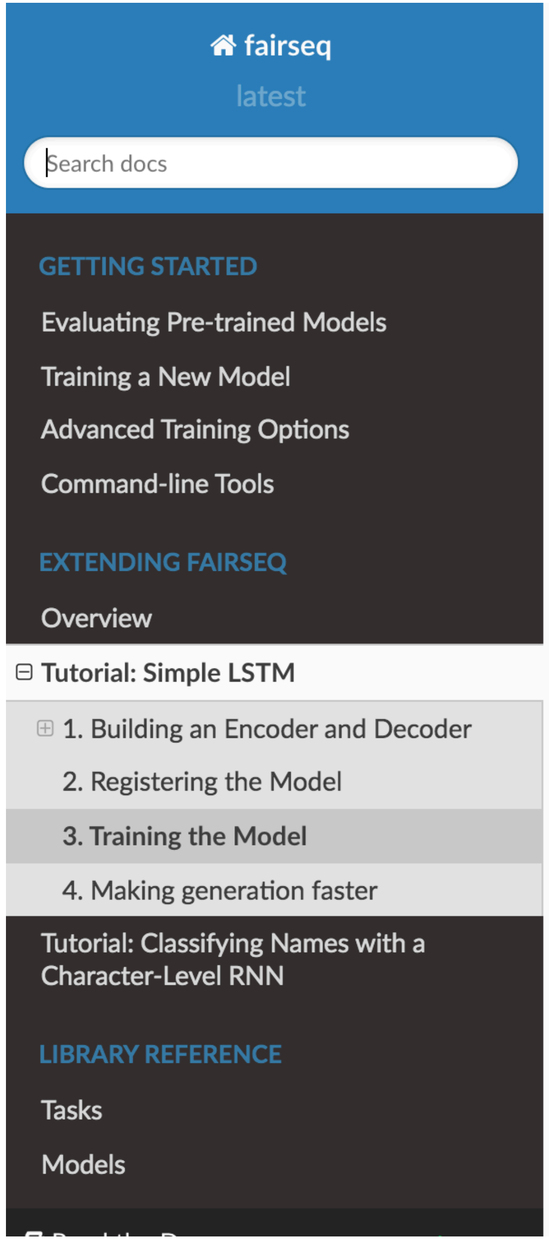
Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length
- Encoder: Can be a CNN/LSTM/…
- Decoder: Execute one step of computation at a time, so computation graph is formulated as taking one input + hidden state. Until reach <STOP>.
- Beam search: can help with lookahead. Finds the (approximate) highest scoring sequence:

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

Implementation Details

- Fairseq:



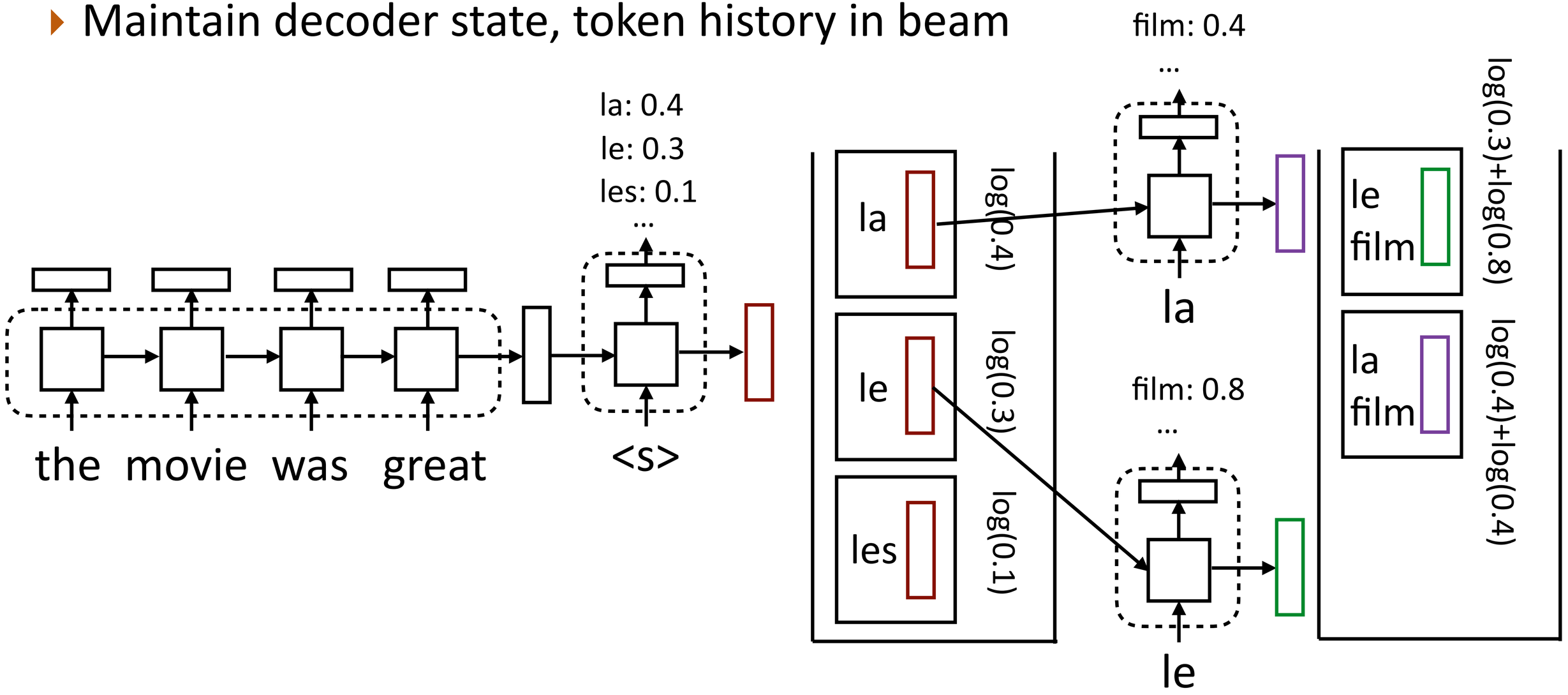
Decoder

Our Decoder will predict the next word, conditioned on the Encoder's final hidden state and an embedded representation of the previous target word – which is sometimes called *teacher forcing*. More specifically, we'll use a `torch.nn.LSTM` to produce a sequence of hidden states that we'll project to the size of the output vocabulary to predict each target word.

```
import torch
from fairseq.models import FairseqDecoder

class SimpleLSTMDecoder(FairseqDecoder):

    def __init__(
        self, dictionary, encoder_hidden_dim=128, embed_dim=128, hidden_dim=128,
        dropout=0.1,
    ):
        super().__init__(dictionary)

        # Our decoder will embed the inputs before feeding them to the LSTM.
        self.embed_tokens = nn.Embedding(
            num_embeddings=len(dictionary),
            embedding_dim=embed_dim,
            padding_idx=dictionary.pad(),
        )
        self.dropout = nn.Dropout(p=dropout)

        # We'll use a single-layer, unidirectional LSTM for simplicity.
        self.lstm = nn.LSTM(
            # For the first layer we'll concatenate the Encoder's final hidden
            # state with the embedded target tokens.
            input_size=encoder_hidden_dim + embed_dim,
            hidden_size=hidden_dim,
            num_layers=1,
            bidirectional=False,
        )

        # Define the output projection.
        self.output_projection = nn.Linear(hidden_dim, len(dictionary))
```

Beam Search

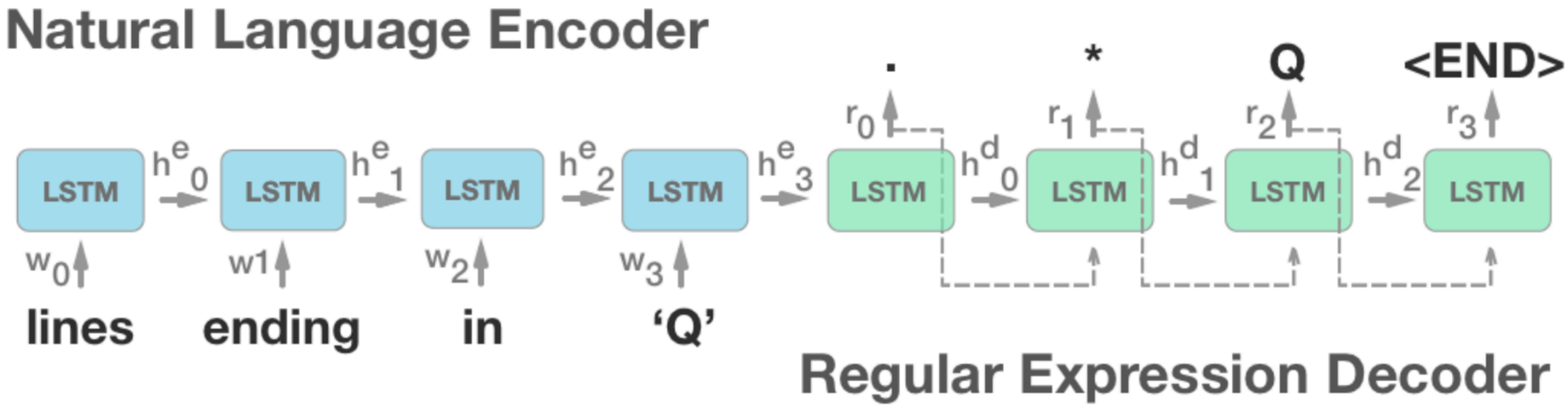
- Maintain decoder state, token history in beam



- Keep **both** *film* states! Hidden state vectors are different

Regex Prediction

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



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

Locascio et al. (2016)

Semantic Parsing as Translation

"what states border Texas"

↓

```
λ x state( x ) ∧ borders( 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)

Semantic Parsing/Lambda Calculus: https://www.youtube.com/watch?v=OocGXG-BY6k&t=200s

SQL Generation

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

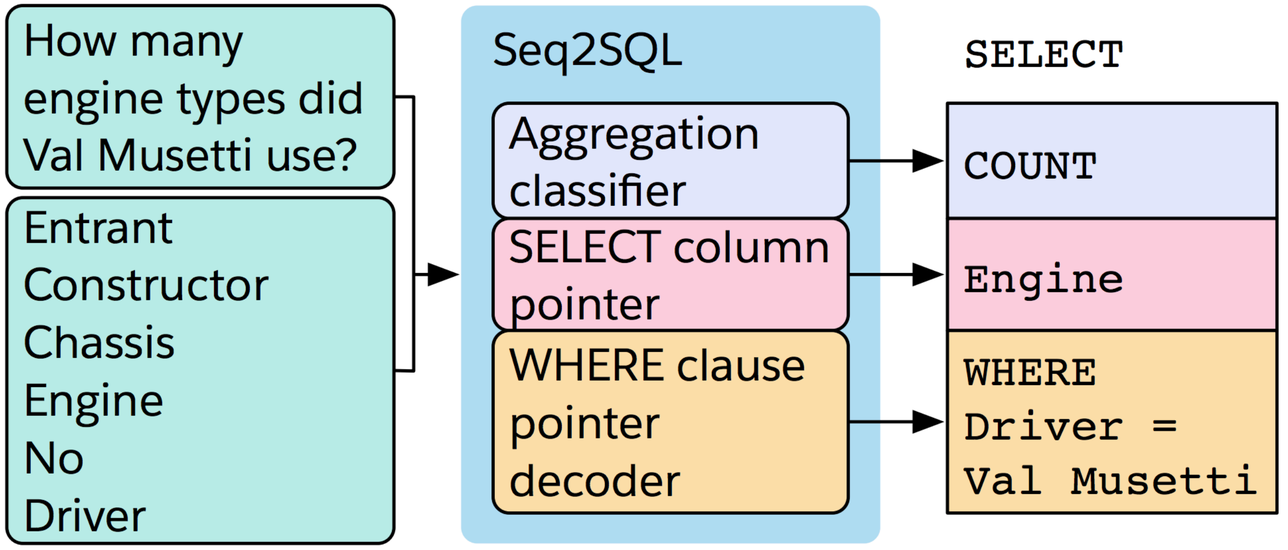
Question:

How many CFL teams are from York College?

SQL:

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

- How to ensure that well-formed SQL is generated?
  - Three components
- How to capture column names + constants?
  - Pointer mechanisms



Zhong et al. (2017)

Attention

Problems with Seq2seq Models

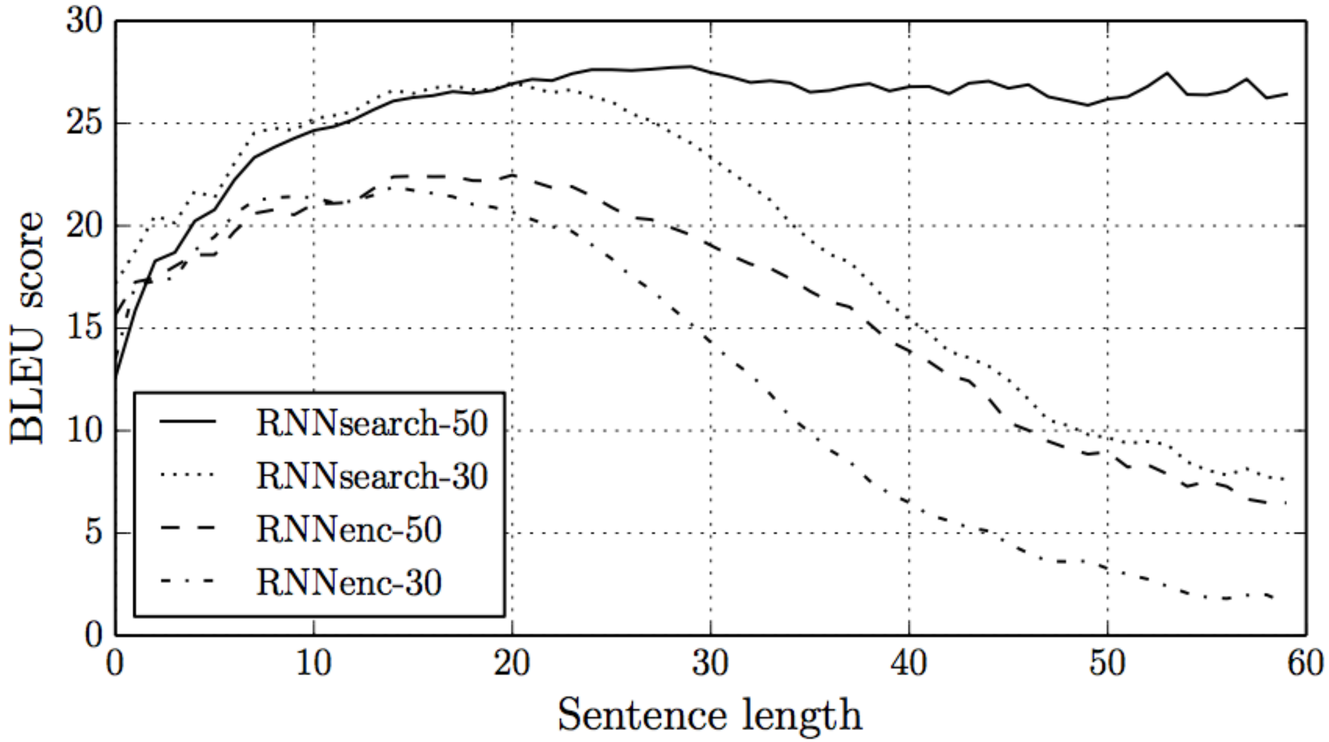
- Encoder-decoder models like to repeat themselves:

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

- Often a byproduct of training these models poorly. Input is forgotten by the LSTM so it gets stuck in a "loop" of generation 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 sentences



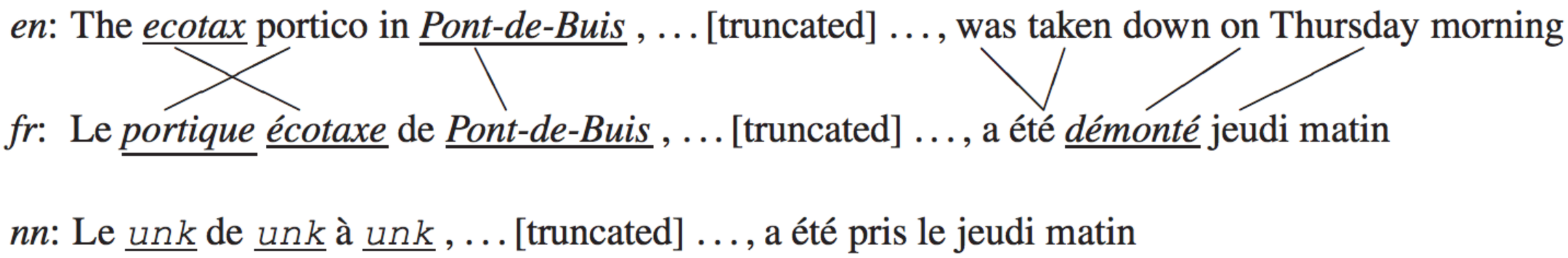
RNNenc: the model we've discussed so far

RNNsearch: uses attention

Bahdanau et al. (2014)

Problems with Seq2seq Models

- Unknown words:

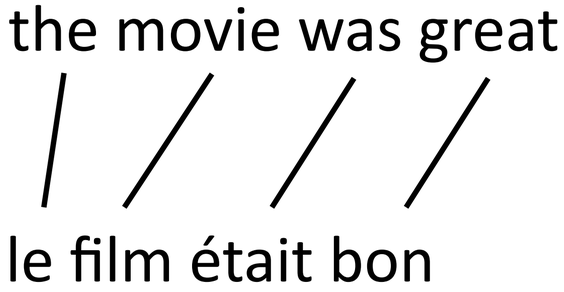


- Encoding these rare words into a vector space is really hard
- In fact, we don't want to encode them, we want a way of directly looking back at the input and copying them (Pont-de-Buis)

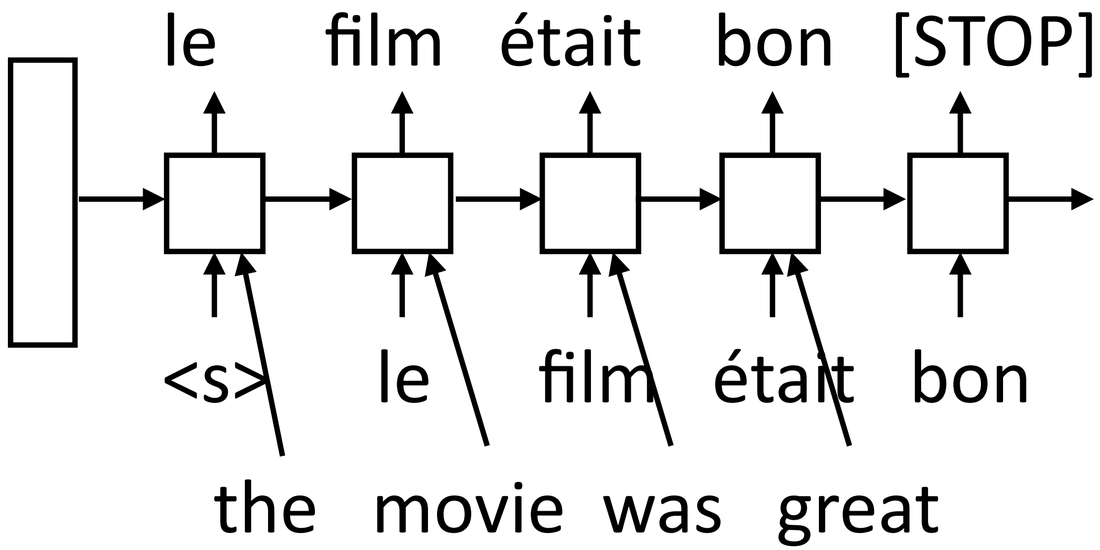
Jean et al. (2015), Luong et al. (2015)

Aligned Inputs

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



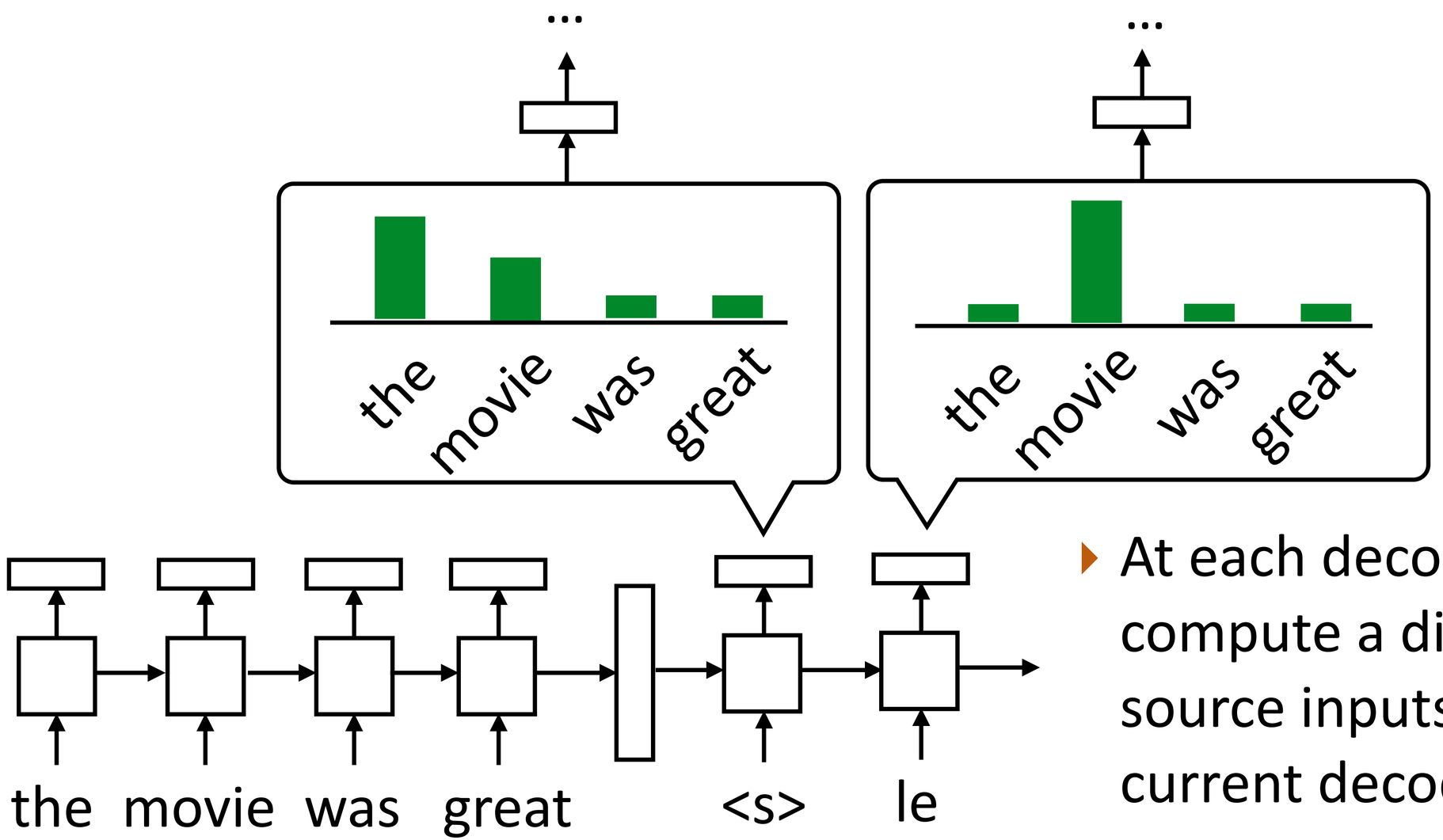
- Can look at the corresponding input word when translating — this could scale!



- Much less burden on the hidden state

- How can we achieve this without hardcoding it?

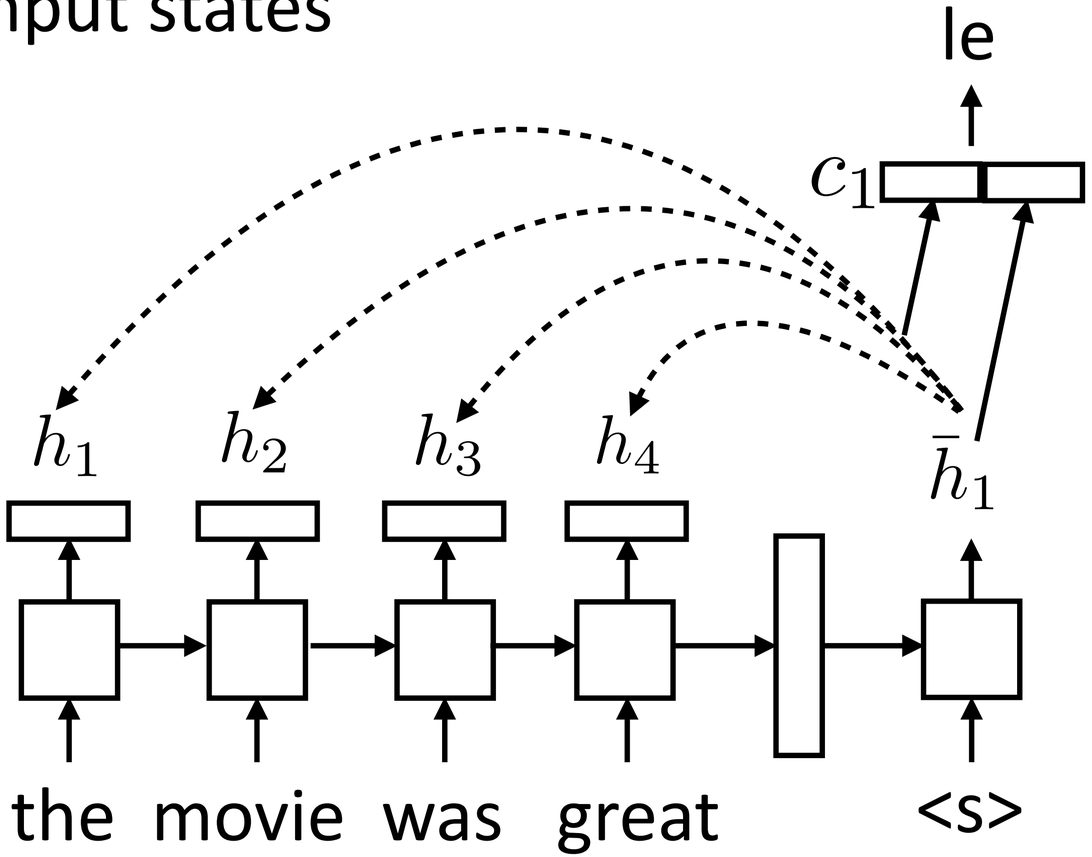
Attention



- 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



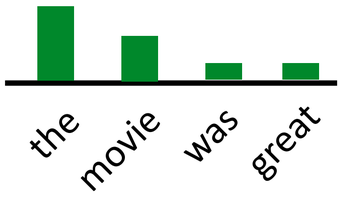
- No attn: $P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h}_i)$

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

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

- Weighted sum of input hidden states (vector)

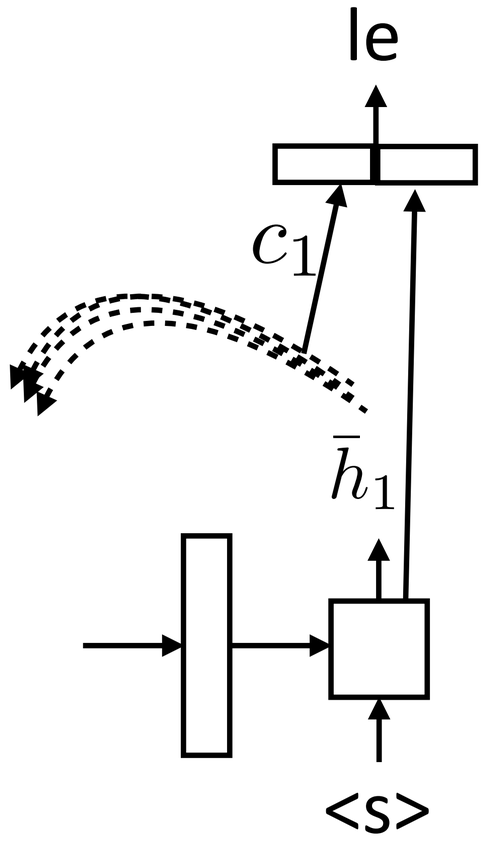
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$



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

- Some function f (next slide)

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

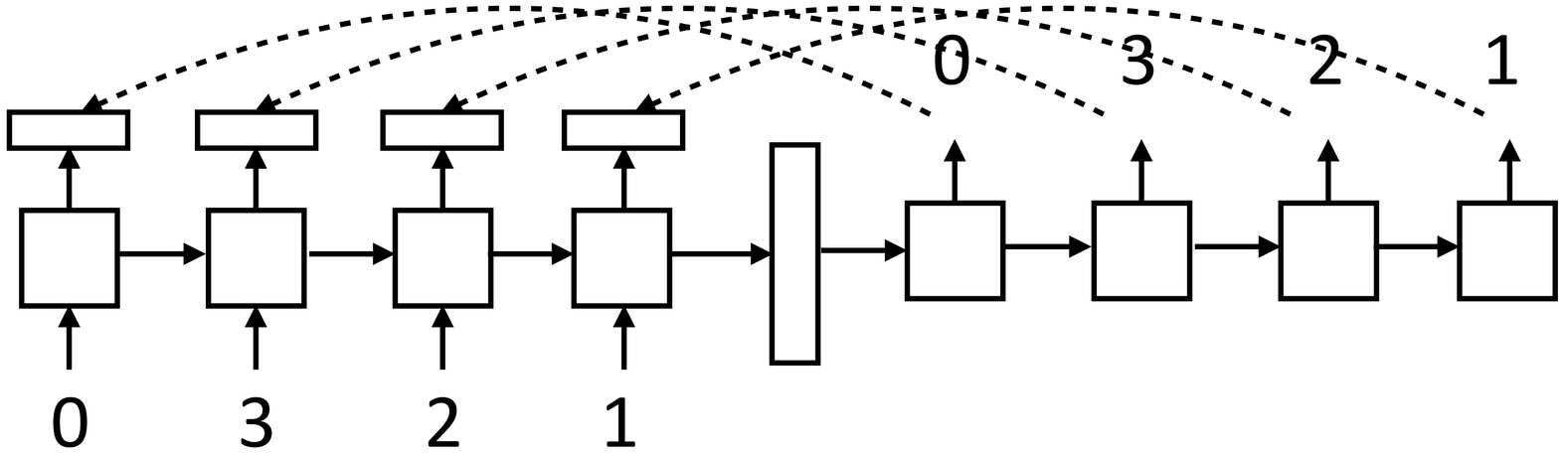
$$f(\bar{h}_i, h_j) = \bar{h}_i^\top W h_j$$

- Luong+ (2015): bilinear

- Note that this all uses outputs of hidden layers

What can attention do?

- Learning to copy — how might this work?



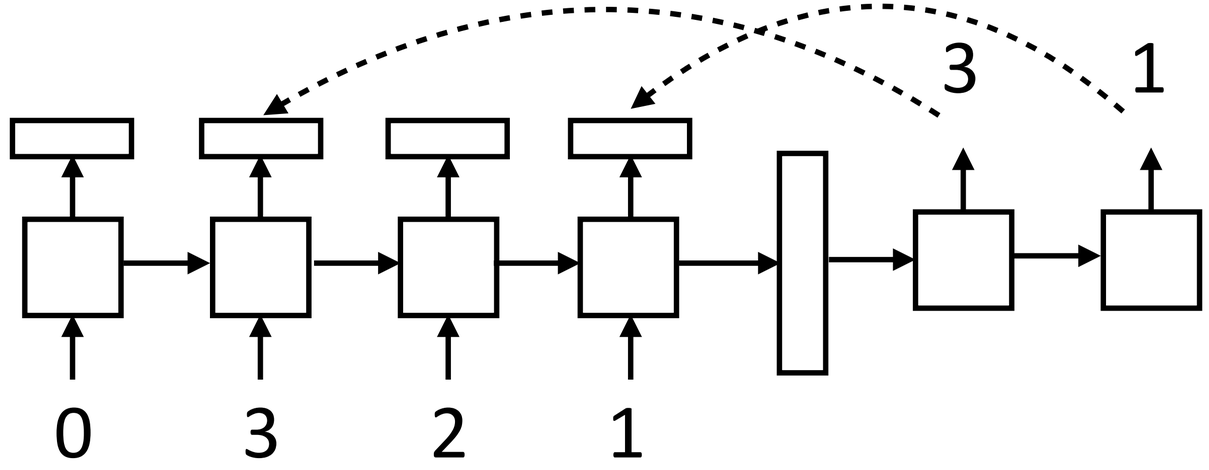
- LSTM can learn to count with the right weight matrix

- This is effectively position-based addressing

Luong et al. (2015)

What can attention do?

- Learning to subsample tokens

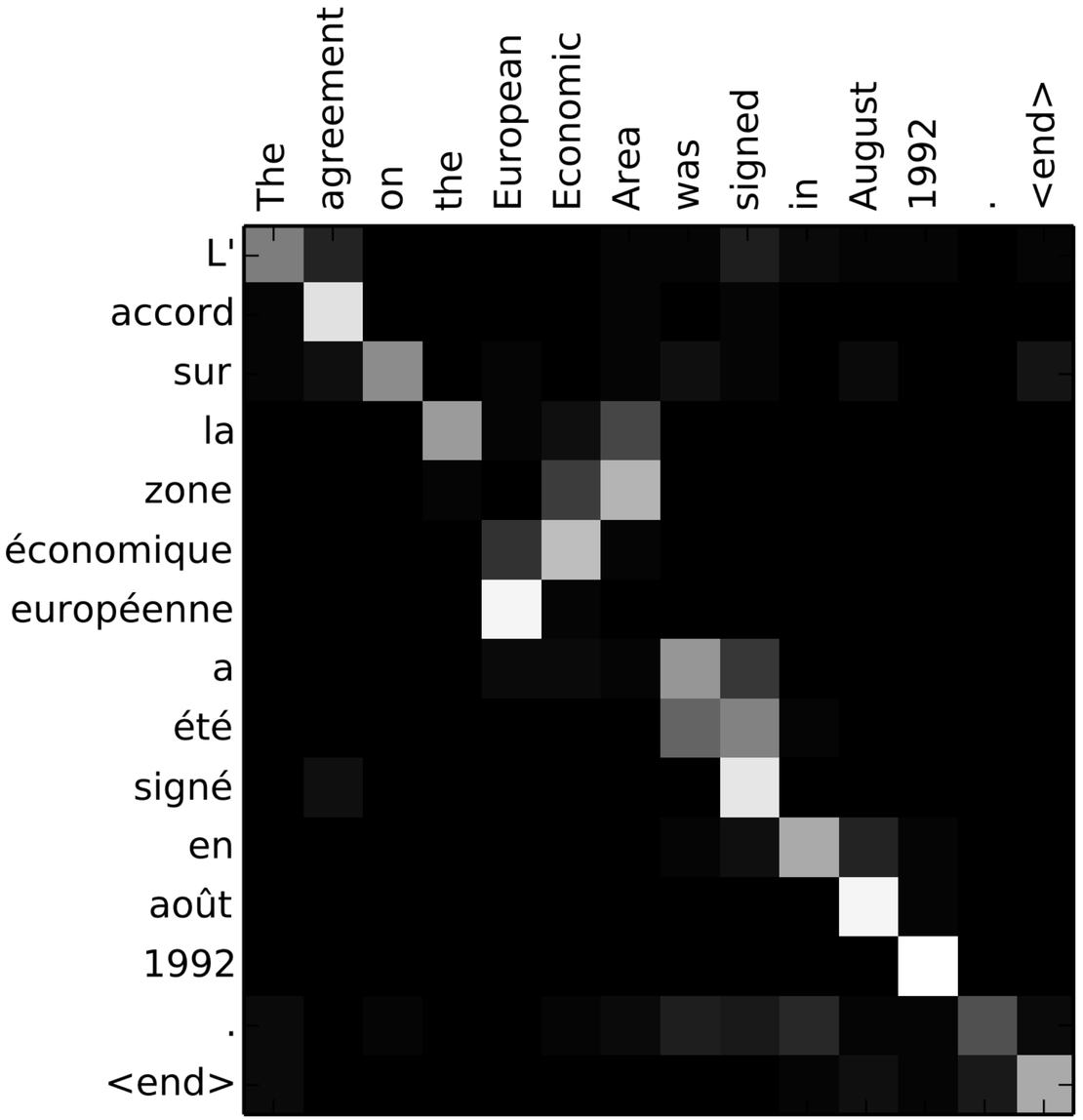


- Need to count (for ordering) and also determine which tokens are in/out
- Content-based addressing

Luong et al. (2015)

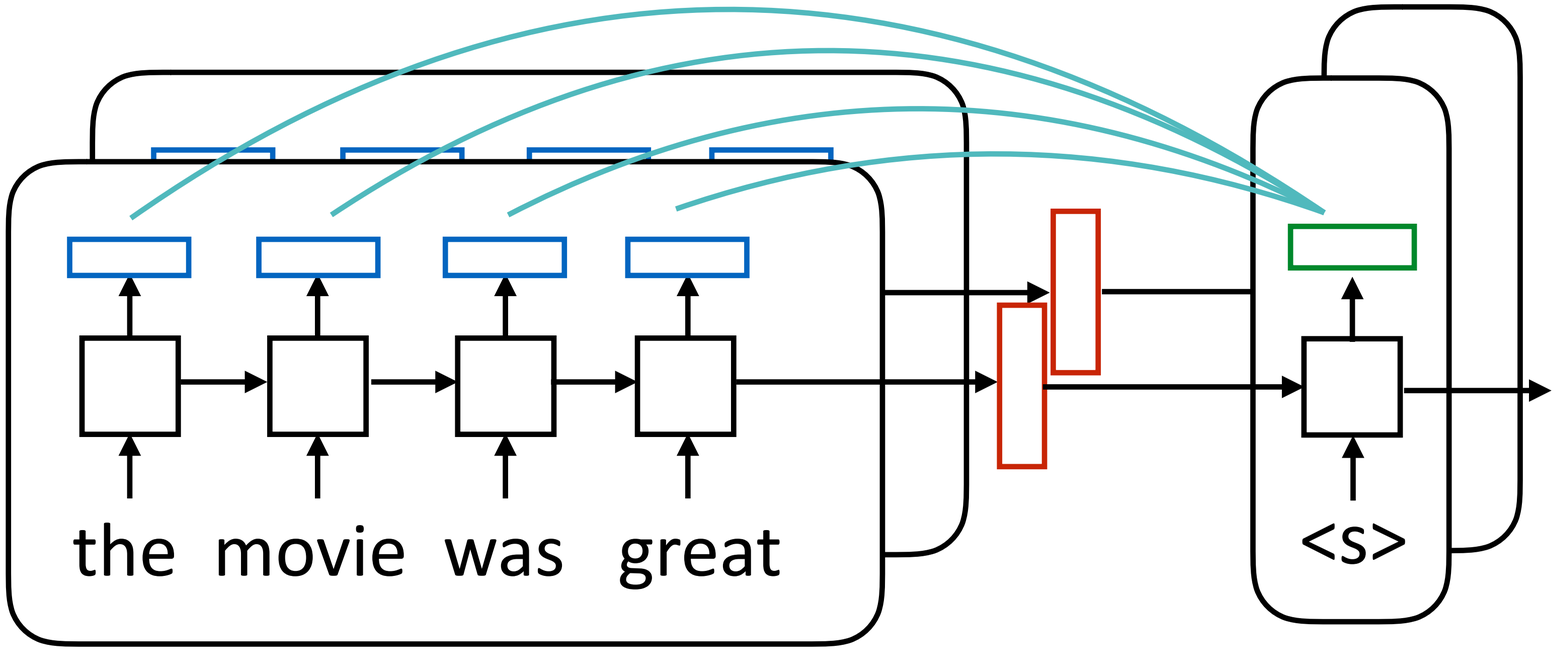
Attention

- 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 dimension



hidden state: batch size x hidden size

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

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

sentence outputs: batch size x hidden size

attention scores = batch size x sentence length

c = batch size x hidden size

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

- Make sure tensors are the right size!

Luong et al. (2015)

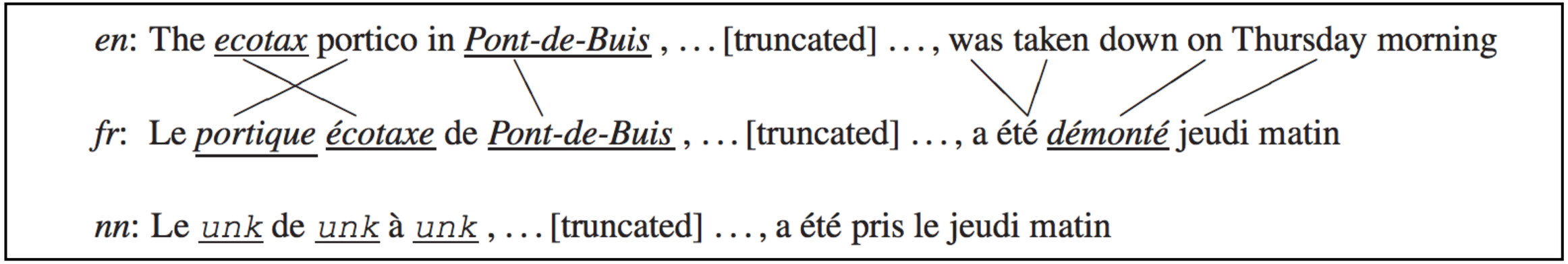
Results

- Machine translation: BLEU score of 14.0 on English-German -> 16.8 with attention, 19.0 with smarter attention (constrained to a small windows)
- Summarization/headline generation: bigram recall from 11% -> 15%
- Semantic parsing: ~30% accuracy -> 70+% accuracy on Geoquery

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

Copying Input/Pointers

Unknown Words



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

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

from attention

from RNN hidden state

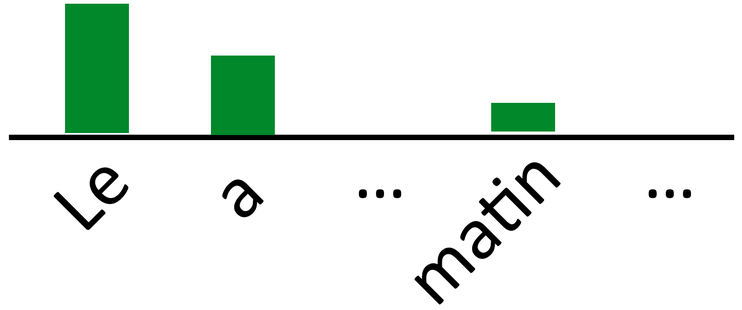
- Problem: target word has to be in the vocabulary, a8enPon + RNN need to generate good embedding to pick it

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

Pointer Network

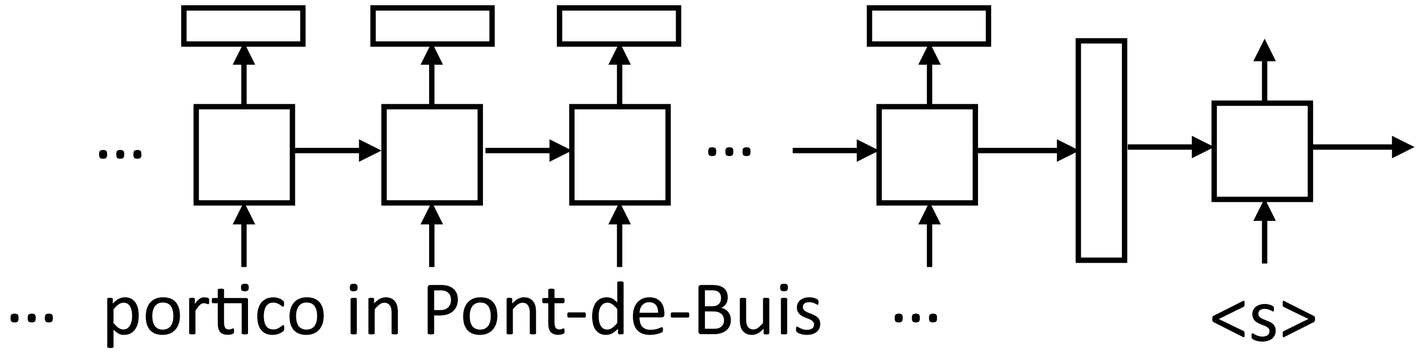
- Standard decoder (P_{vocab}): softmax over vocabulary

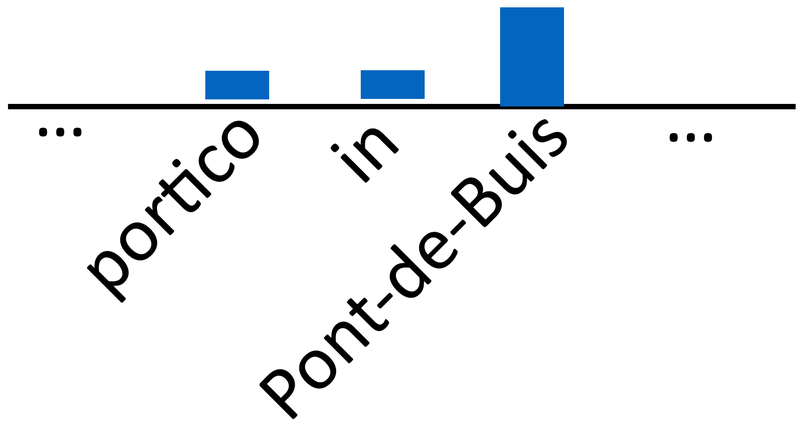
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W[c_i; \bar{h}_i])$$



- Pointer network (P_{pointer}): predict from *source* words, instead of target vocabulary

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





Pointer Generator Mixture Models

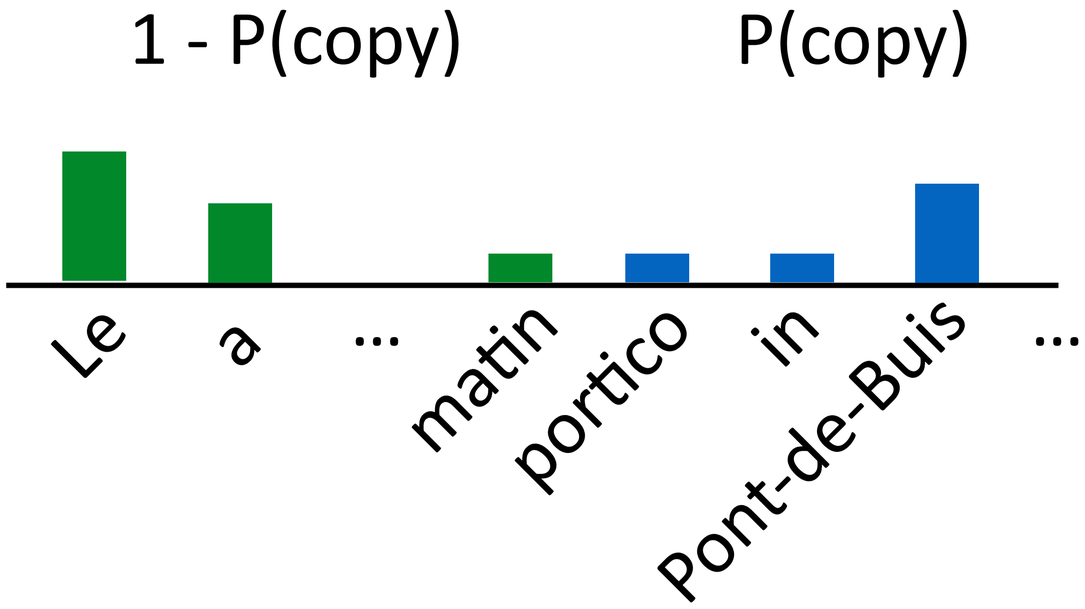
- Define the decoder model as a mixture model of P_{vocab} and P_{pointer}

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

- Predict P(copy) based on decoder state, input, etc.

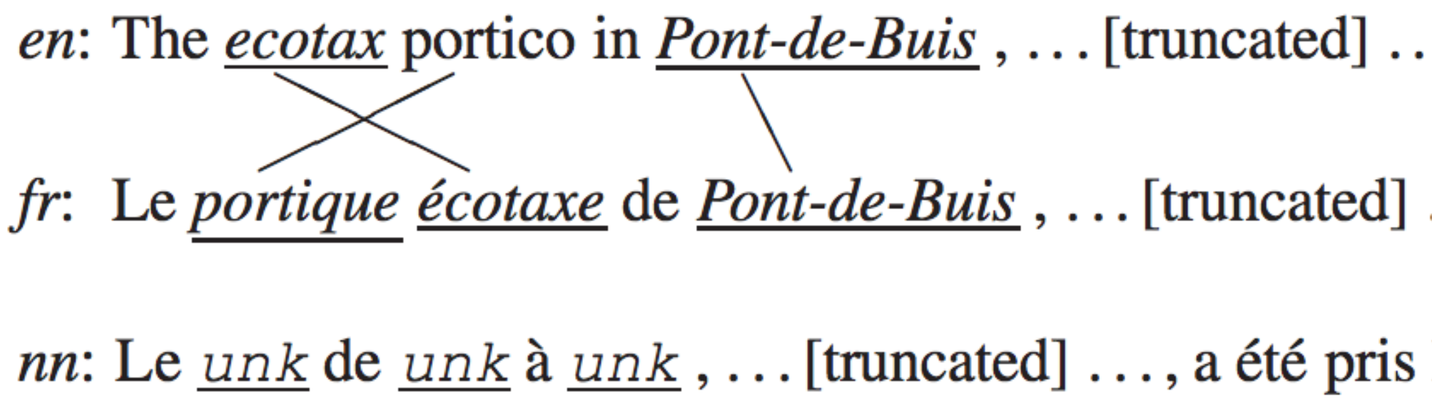
- Marginalize over copy variable during training and inference

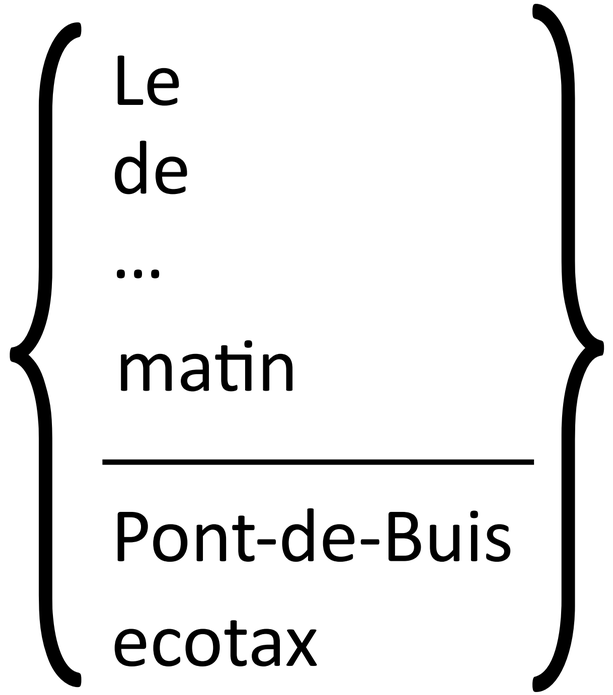
- Model will be able to both generate and copy, flexibly adapt between the two



Gulcehre et al. (2016), Gu et al. (2016)

Copying



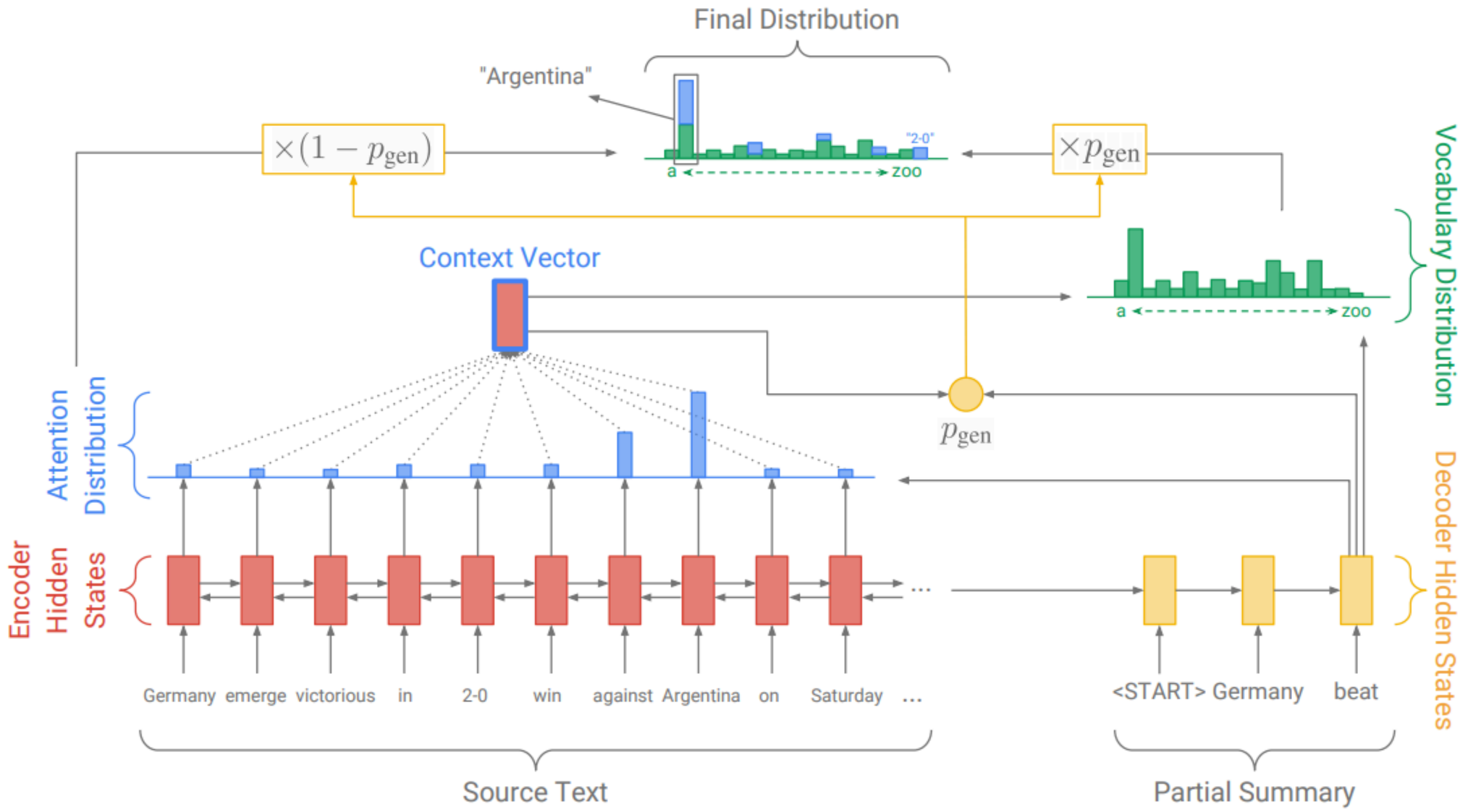


- Vocabulary contains "normal" vocab as well as words in input. Normalizes over both of these:

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

- Bilinear function of input representation + output hidden state

Copying in Summarization



See et al. (2017)

Copying in Summarization

	ROUGE			METEOR	
	1	2	L	exact match	+ stem/syn/para
abstractive model (Nallapati et al., 2016)*	35.46	13.30	32.65	-	-
seq-to-seq + attn baseline (150k vocab)	30.49	11.17	28.08	11.65	12.86
seq-to-seq + attn baseline (50k vocab)	31.33	11.81	28.83	12.03	13.20
pointer-generator	36.44	15.66	33.42	15.35	16.65
pointer-generator + coverage	**39.53**	**17.28**	**36.38**	17.32	18.72
lead-3 baseline (ours)	40.34	17.70	36.57	20.48	22.21
lead-3 baseline (Nallapati et al., 2017)*	39.2	15.7	35.5	-	-
extractive model (Nallapati et al., 2017)*	39.6	16.2	35.3	-	-

See et al. (2017)

Copying in Summarization

Original Text (truncated): lagos, nigeria (cnn) a day after winning nigeria's presidency, ***muhammadu buhari*** told cnn's christiane amanpour that **he plans to aggressively fight corruption that has long plagued nigeria** and go after the root of the nation's unrest. *buhari* said he'll "rapidly give attention" to curbing violence in the northeast part of nigeria, where the terrorist group boko haram operates. by cooperating with neighboring nations chad, cameroon and niger, **he said his administration is confident it will be able to thwart criminals** and others contributing to nigeria's instability. for the first time in nigeria's history, the opposition defeated the ruling party in democratic elections. *buhari* defeated incumbent goodluck jonathan by about 2 million votes, according to nigeria's independent national electoral commission. **the win comes after a long history of military rule, coups and botched attempts at democracy in africa's most populous nation.**

Baseline Seq2Seq + Attention: **UNK UNK** says his administration is confident it will be able to **destabilize nigeria's economy**. **UNK** says his administration is confident it will be able to thwart criminals and other **nigerians**. **he says the country has long nigeria and nigeria's economy.**

Pointer-Gen: *muhammadu buhari* says he plans to aggressively fight corruption **in the northeast part of nigeria**. he says he'll "rapidly give attention" to curbing violence **in the northeast part of nigeria**. he says his administration is confident it will be able to thwart criminals.

Pointer-Gen + Coverage: *muhammadu buhari* says he plans to aggressively fight corruption that has long plagued nigeria. he says his administration is confident it will be able to thwart criminals. the win comes after a long history of military rule, coups and botched attempts at democracy in africa's most populous nation.

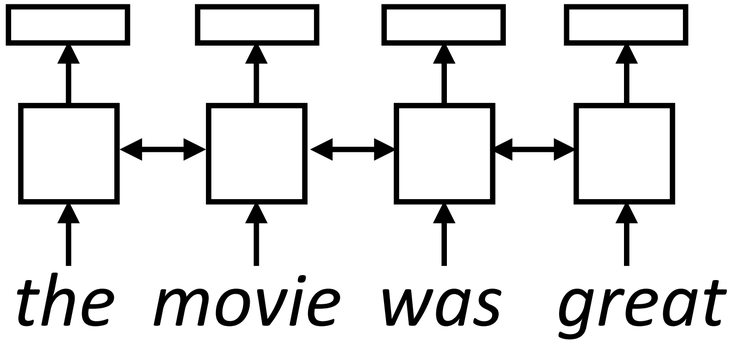
Figure 1: Comparison of output of 3 abstractive summarization models on a news article. The baseline model makes **factual errors**, a **nonsensical sentence** and struggles with OOV words *muhammadu buhari*. The pointer-generator model is accurate but **repeats itself**. Coverage eliminates repetition. The final summary is composed from **several fragments**.

See et al. (2017)

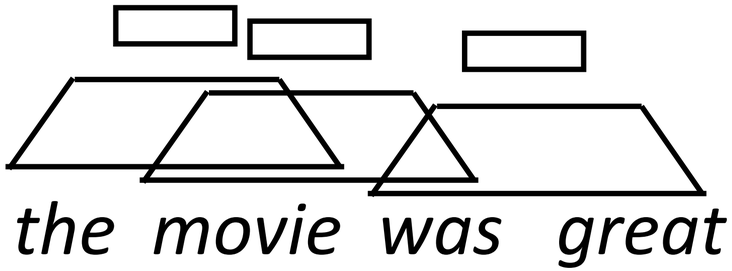
Transformers

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?

- 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

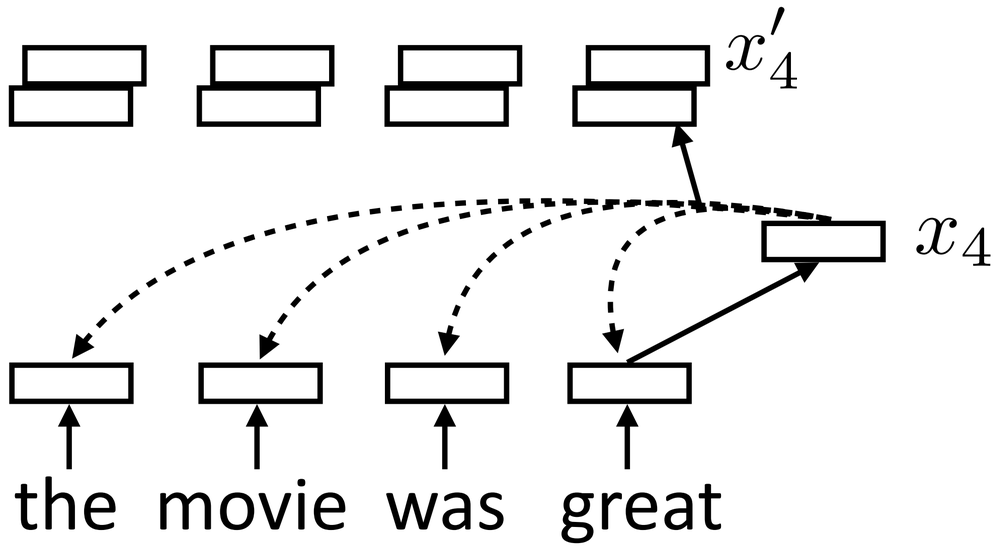
Vaswani et al. (2017)

Self-Attention

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

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

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



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

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

Vaswani et al. (2017)

What can self-attention do?

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

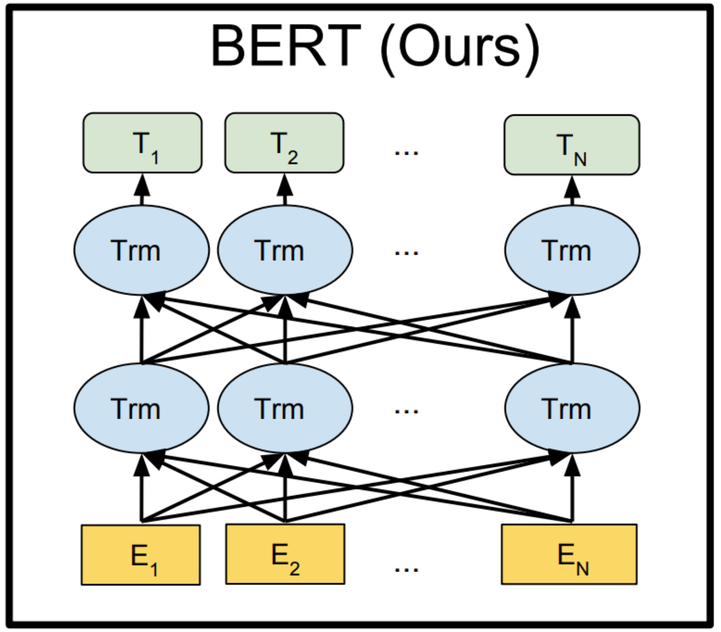
0	0.1	0	0	0	0	0	0	0.5	0	0.4	0

- 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
- Used for tasks including data-to-text generation and summarization
- Explicitly copying input can be beneficial as well
- Transformers are strong models we'll come back to later, if time