CS388: Natural Language Processing

Lecture 15: Semantics II / Seq2seq I

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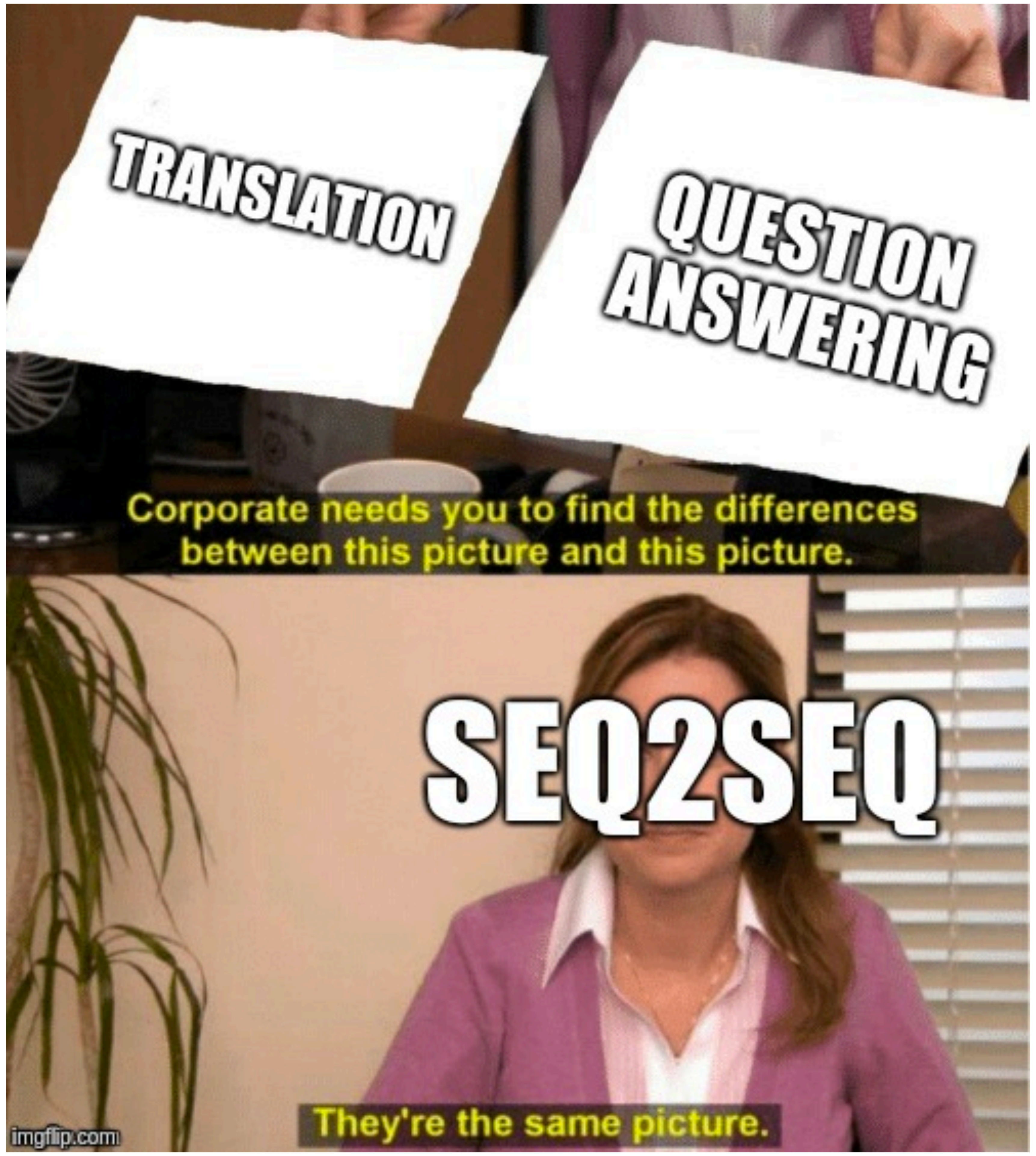

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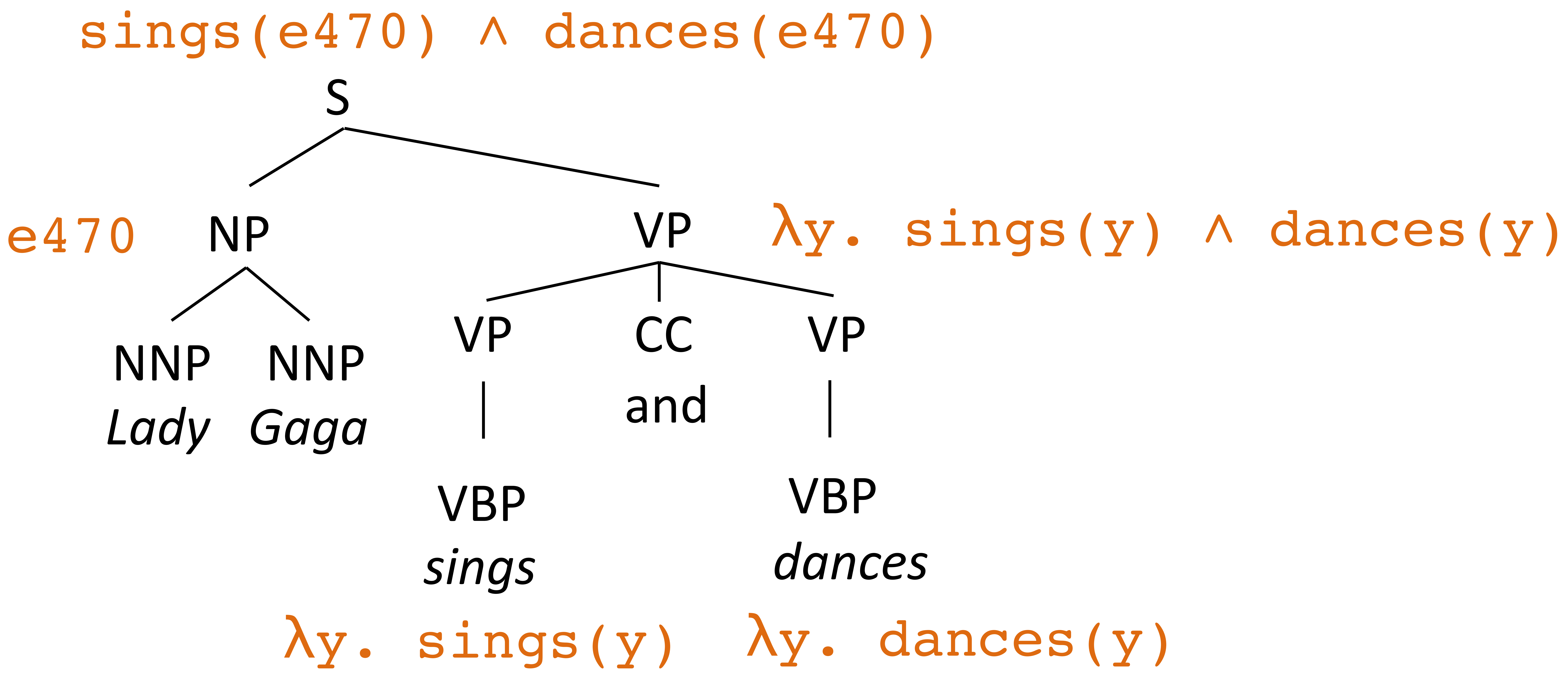
Administrivia

- Project 2 out today
- Mini 2 graded by tomorrow
- Final project feedback soon

Recall: Parses to Logical Forms

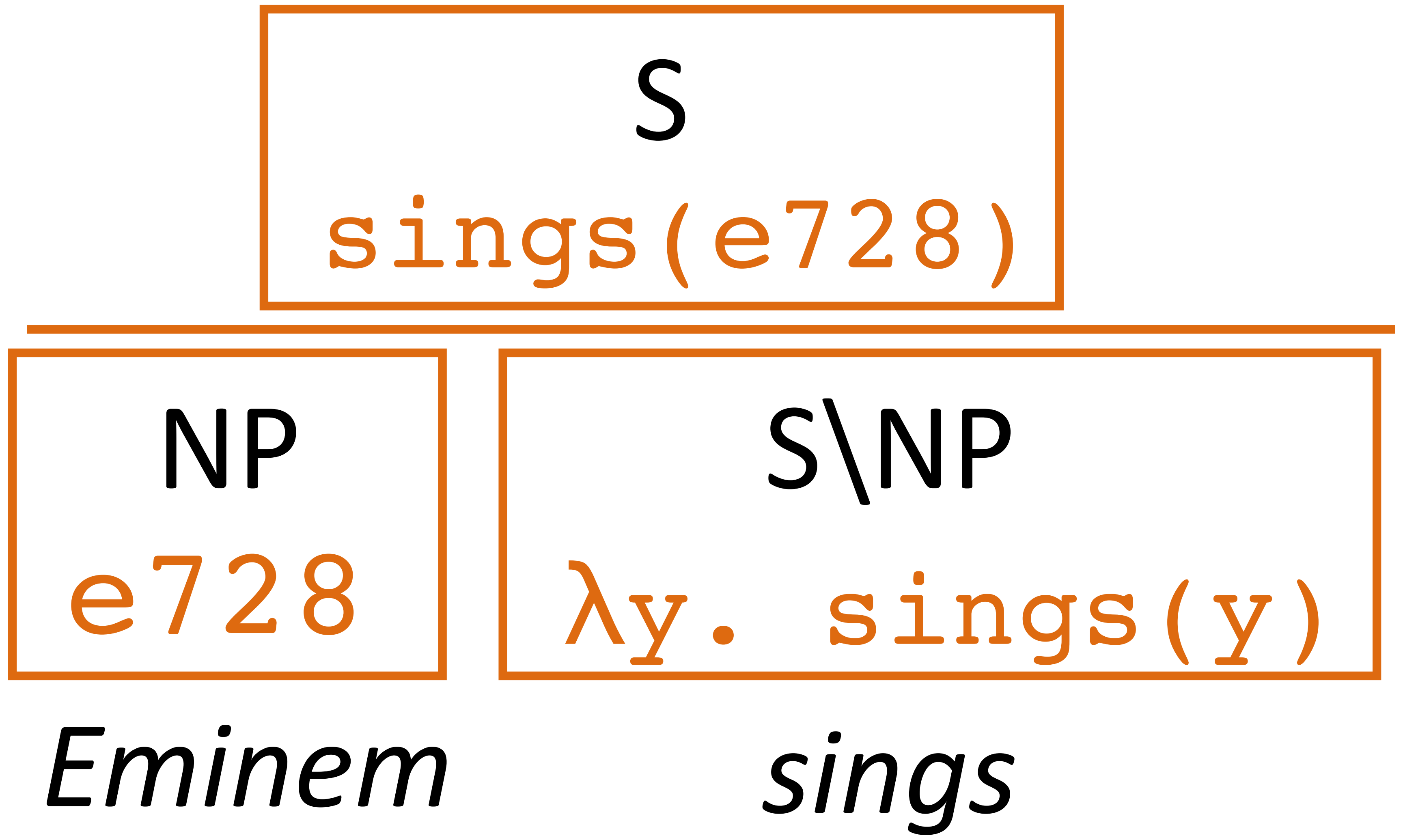


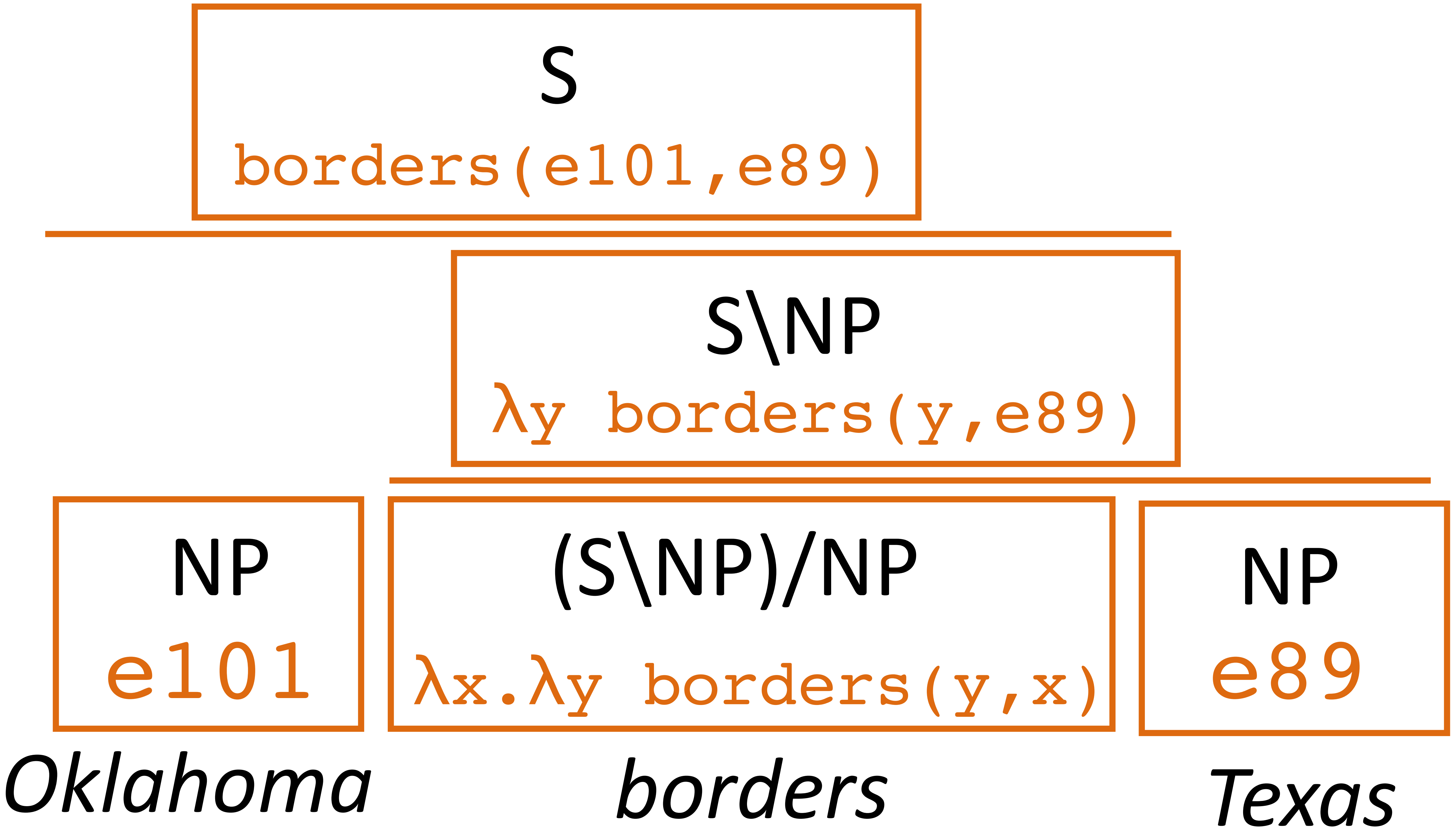
- General rules: VP: $\lambda y.\ a(y) \wedge b(y)$ -> VP: $\lambda y.\ a(y)$ CC VP: $\lambda y.\ b(y)$

  S: $f(x)$ -> NP: x VP: f

Recall: CCG

- Steedman+Szabolcsi 1980s: formalism bridging syntax and semantics
- Syntactic categories (for this lecture): S, NP, "slash" categories
  - S\NP: "if I combine with an NP on my left side, I form a sentence" — verb
  - (S\NP)/NP: "I need an NP on my right and then on my left" — verb with a direct object





This Lecture

- Seq2seq models
- Seq2seq models for semantic parsing
- Intro to attention

Encoder-Decoder Models

Motivation

- Parsers have been pretty hard to build…
  - Constituency/graph-based: complex dynamic programs
  - Transition-based: complex transition systems
  - CCG/semantic parsers: complex syntax/semantics interface, challenging inference, challenging learning
- For semantic parsing in particular: bridging the syntax-semantics divide results in structural weirdnesses in parsers, hard to learn the right semantic grammar
- Encoder-decoder models can (in principle) predict any linearized sequence of tokens

Encoder-Decoder

- Semantic parsing:

What states border Texas ⟶ `λ x state( x ) ∧ borders( x , e89 )`

- Syntactic parsing

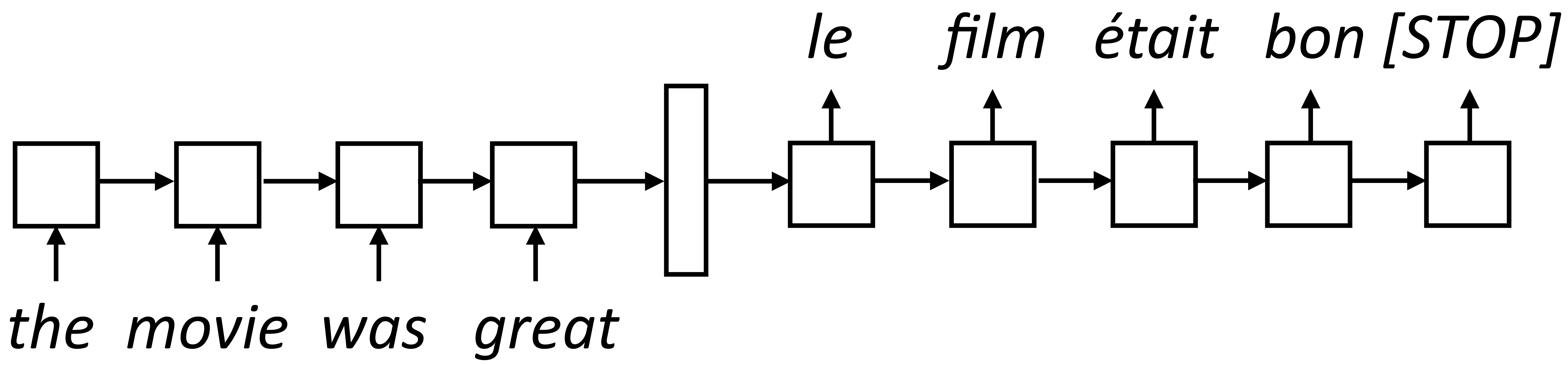
The dog ran ⟶ `(S (NP (DT the) (NN dog) ) (VP (VBD ran) ) )`

(but what if we produce an invalid tree or one with different words?) 🤔

- Machine translation, summarization, dialogue can all be viewed in this framework as well

Encoder-Decoder

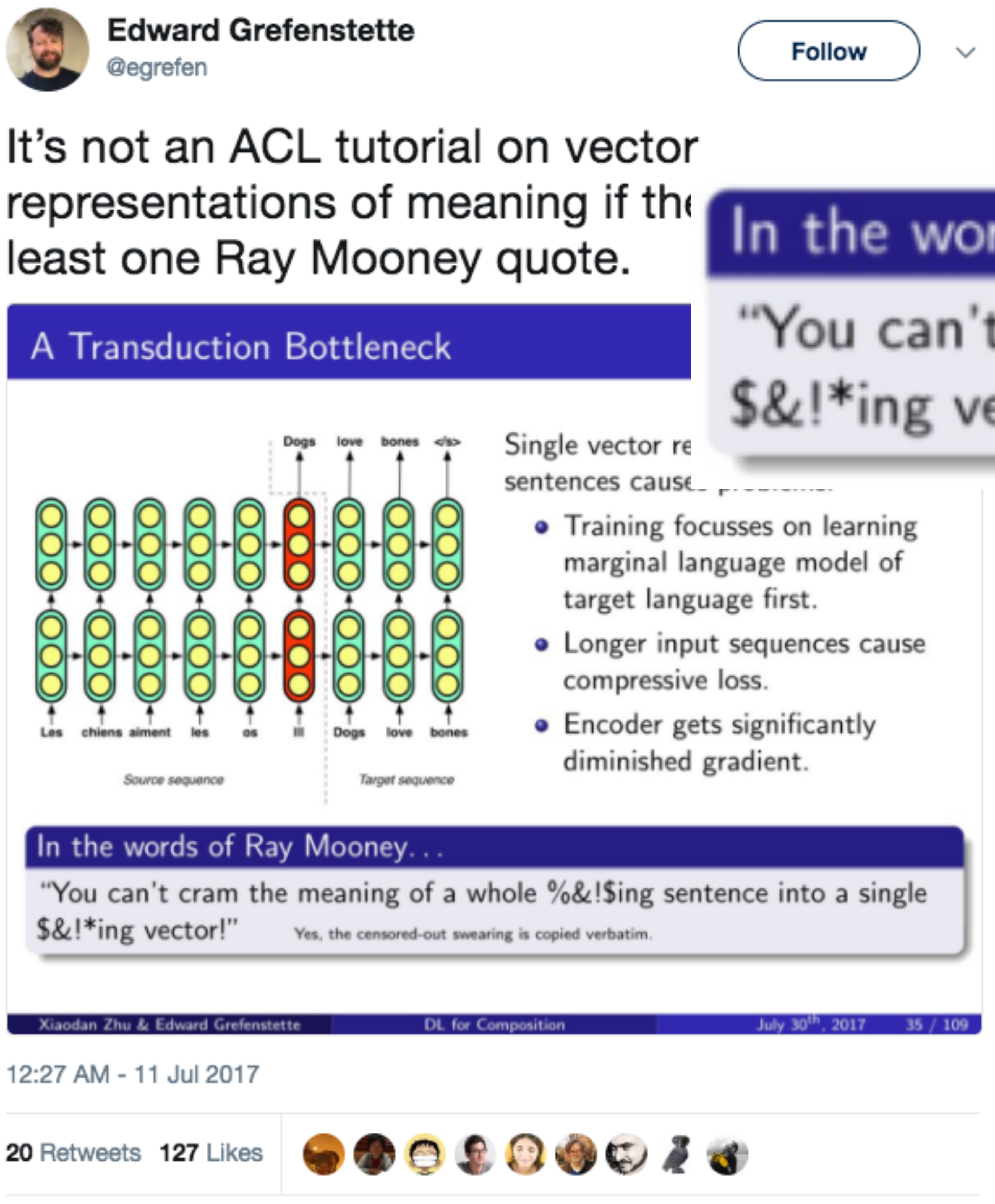
- Encode a sequence into a fixed-sized vector

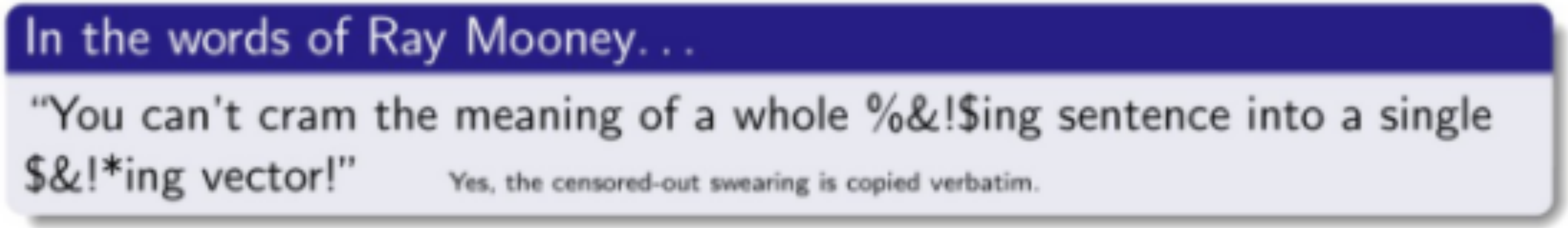


- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

Encoder-Decoder



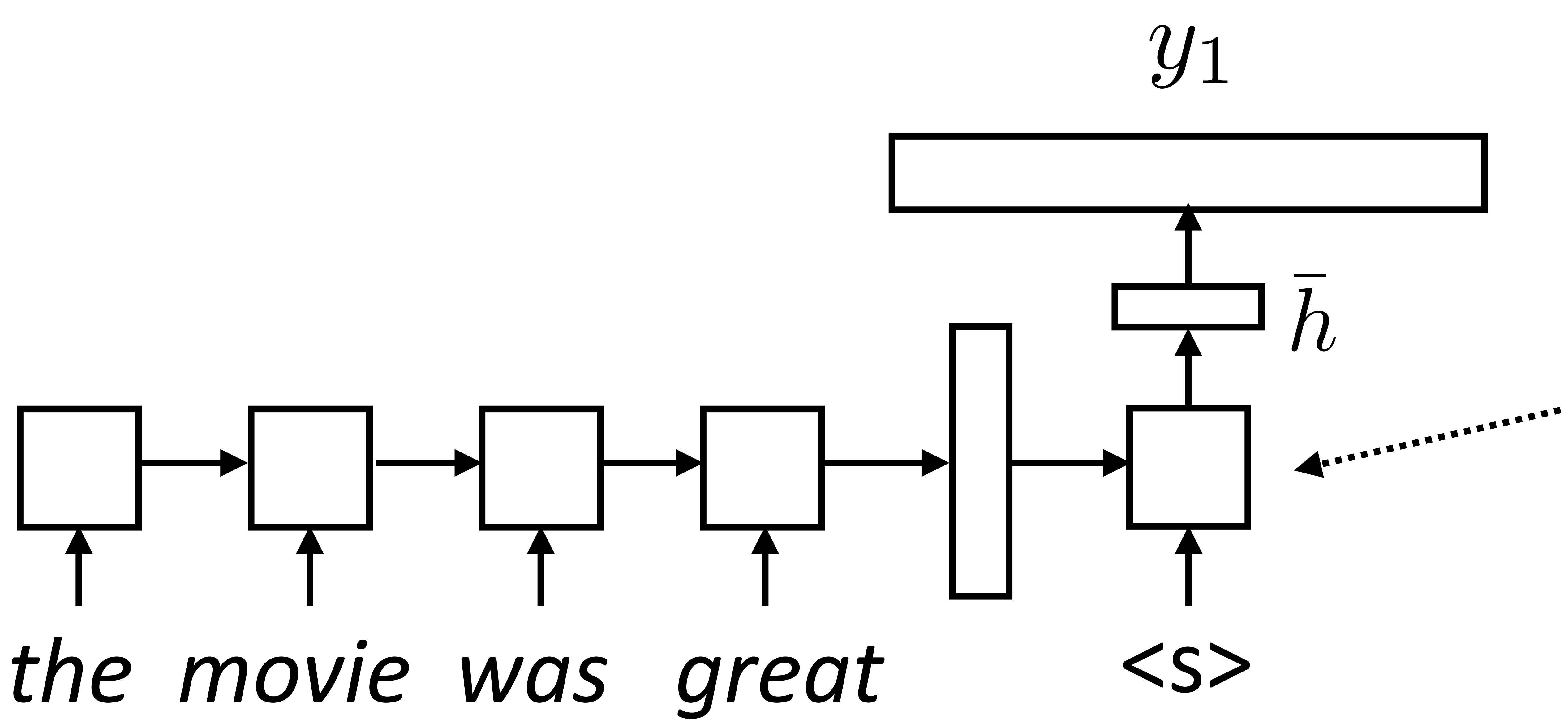


- Is this true? Sort of...we'll come back to this later

Model

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

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



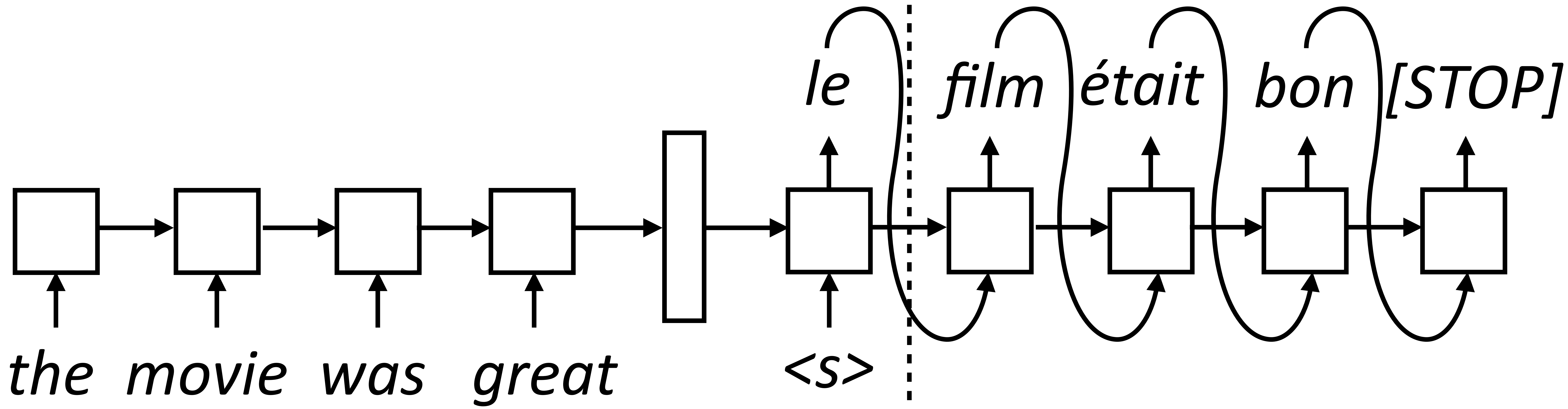
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W\bar{h})$$

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

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

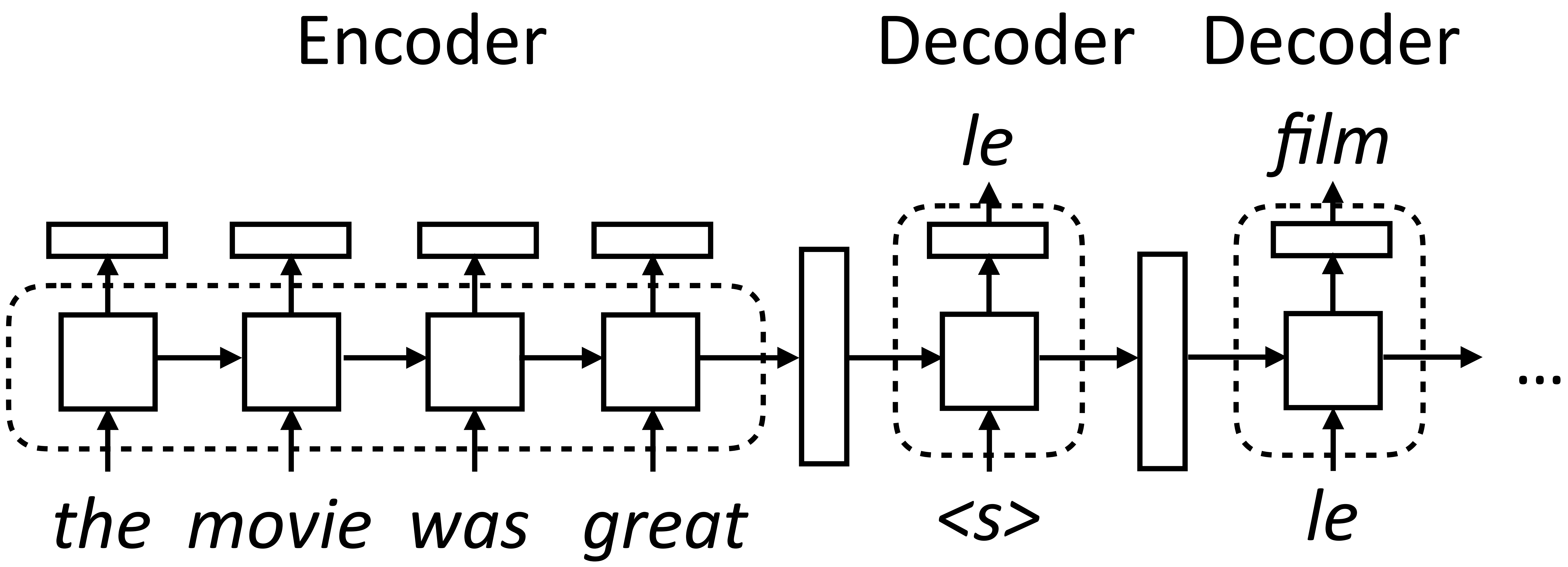
Inference

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



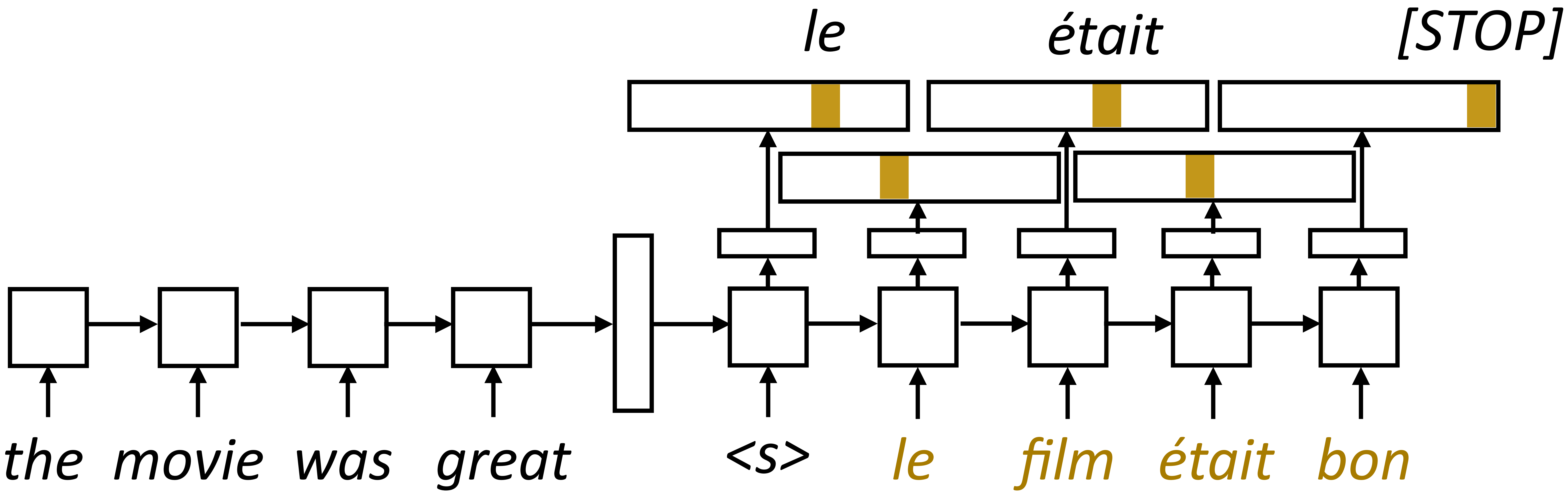
- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

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

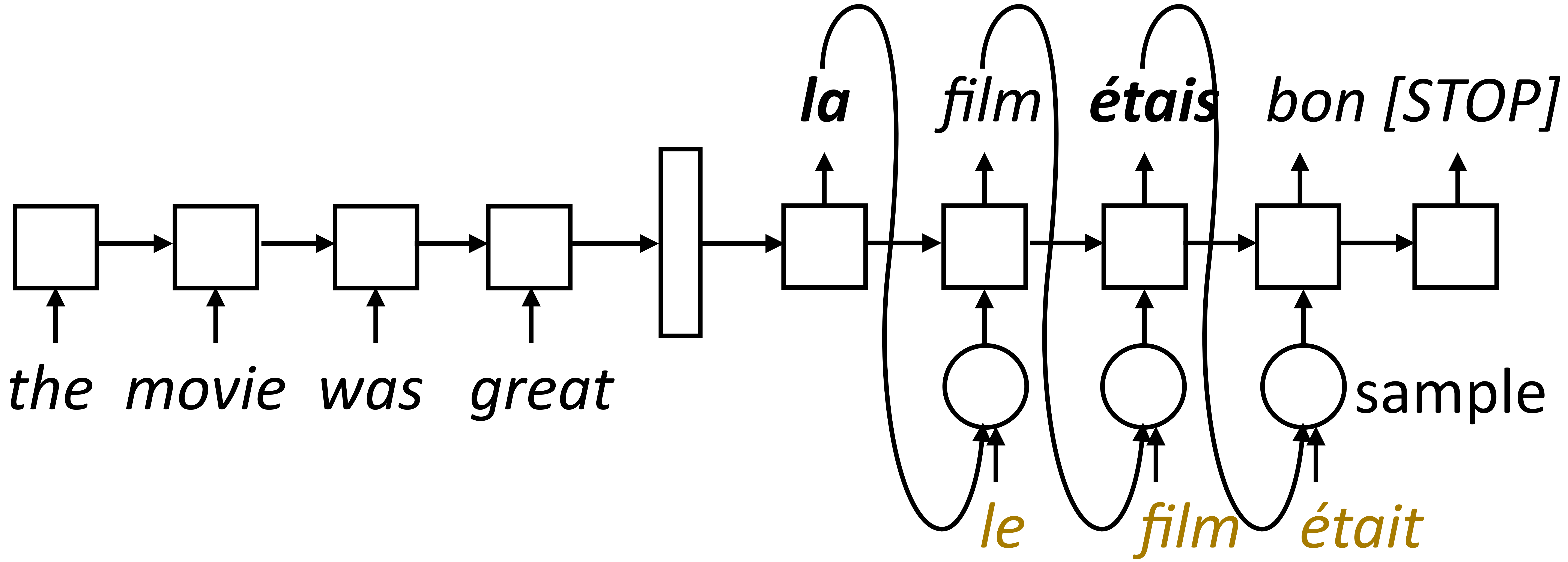
Training



- 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 (called "teacher forcing")

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 (teacher forcing) and decaying it works best
- "Right" thing: train with reinforcement learning

Bengio et al. (2015)

Implementation Details

- Sentence lengths vary for both encoder and decoder:
  - Typically pad everything to the right length and use a mask or indexing to access a subset of terms
- Encoder: looks like what you did in Mini 2
- Decoder: execute one step of computation at a time, so computation graph is formulated as taking one input + hidden state
  - Test time: do this until you generate the stop token
  - Training: do this until you reach the gold stopping point

Implementation Details (cont'd)

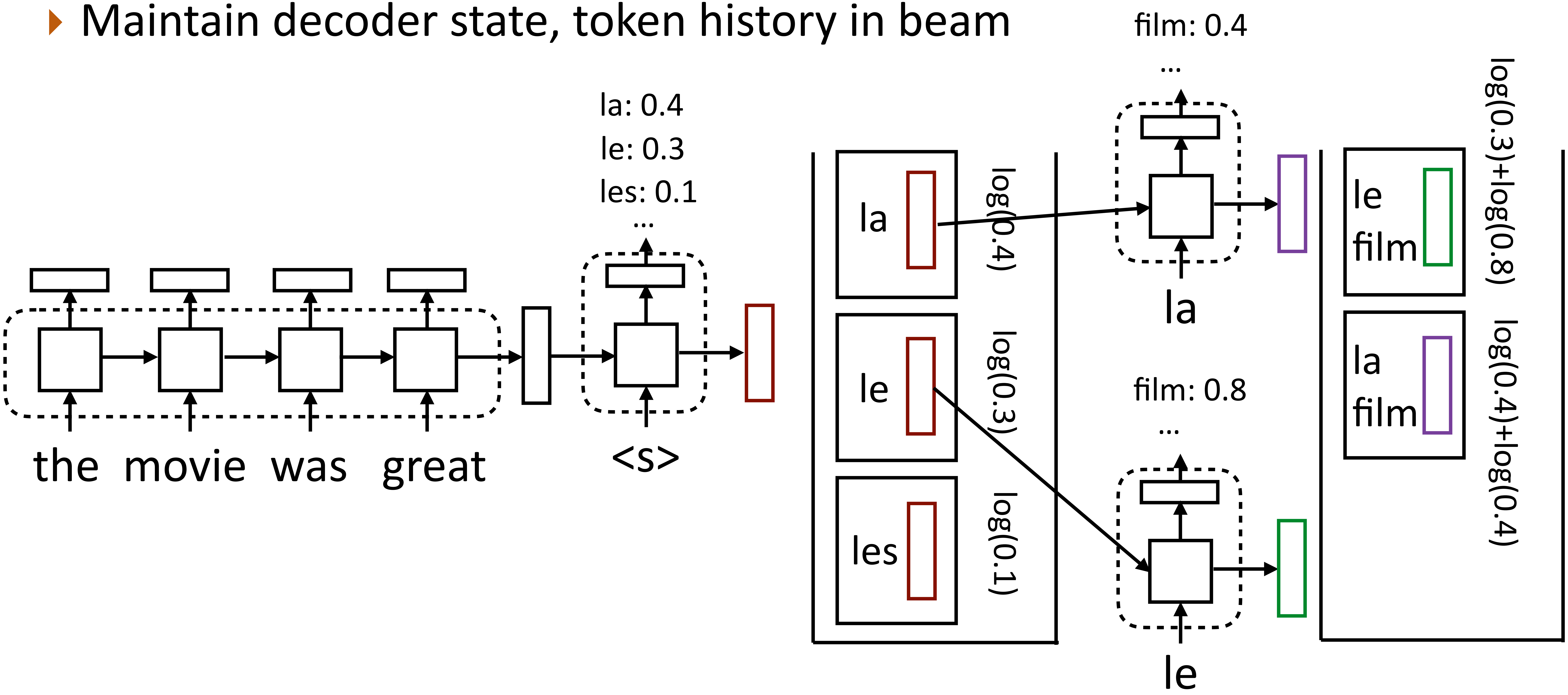
- Batching is pretty tricky: decoder is across time steps, so you probably want your label vectors to look like [num timesteps x batch size x num labels], iterate upwards by time steps

- 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



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

Other Architectures

- What's the basic abstraction here?
  - Encoder: sentence -> vector
  - Decoder: hidden state, output prefix -> new hidden state, new output
    - OR: sentence, output prefix -> new output (more general)
- Wide variety of models can apply here: CNN encoders, decoders can be any autoregressive model including certain types of CNNs
- Transformer: another model discussed next lecture

Seq2seq Semantic Parsing

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
- What are some benefits of this approach compared to grammar-based?
- What might be some concerns about this approach? How do we mitigate them?

Jia and Liang (2016)

Handling Invariances

"what states border Texas" *"what states border Ohio"*

- Parsing-based approaches handle these the same way
  - Possible divergences: features, different weights in the lexicon
- Can we get seq2seq semantic parsers to handle these the same way?
- Key idea: don't change the model, change the data
- "Data augmentation": encode invariances by automatically generating new training examples

Data Augmentation

Jia and Liang (2016)

Examples

("*what states border texas ?*",

`answer(NV, (state(V0), next_to(V0, NV), const(V0, stateid(texas)))))`

Rules created by ABSENTITIES

ROOT → ⟨ "*what states border* STATEID *?*",

`answer(NV, (state(V0), next_to(V0, NV), const(V0, stateid(`STATEID`)))))`⟩

STATEID → ⟨ "*texas*", `texas` ⟩

STATEID → ⟨"*ohio*", `ohio`⟩

- Lets us synthesize a "*what states border ohio ?*" example
- Abstract out entities: now we can "remix" examples and encode invariance to entity ID. More complicated remixes too

Semantic Parsing as Translation

GEO
x: “*what is the population of iowa ?*”
```
y: _answer ( NV , (
  _population ( NV , V1 ) , _const (
    V0 , _stateid ( iowa ) ) ) )
```

ATIS
x: “*can you list all flights from chicago to milwaukee*”
```
y: ( _lambda $0 e ( _and
   ( _flight $0 )
   ( _from $0 chicago : _ci )
   ( _to $0 milwaukee : _ci ) ) )
```

Overnight
x: “*when is the weekly standup*”
```
y: ( call listValue ( call
    getProperty meeting.weekly_standup
    ( string start_time ) ) )
```

- Prolog
- Lambda calculus
- Other DSLs

- Handle all of these with uniform machinery!

Jia and Liang (2016)

Semantic Parsing as Translation

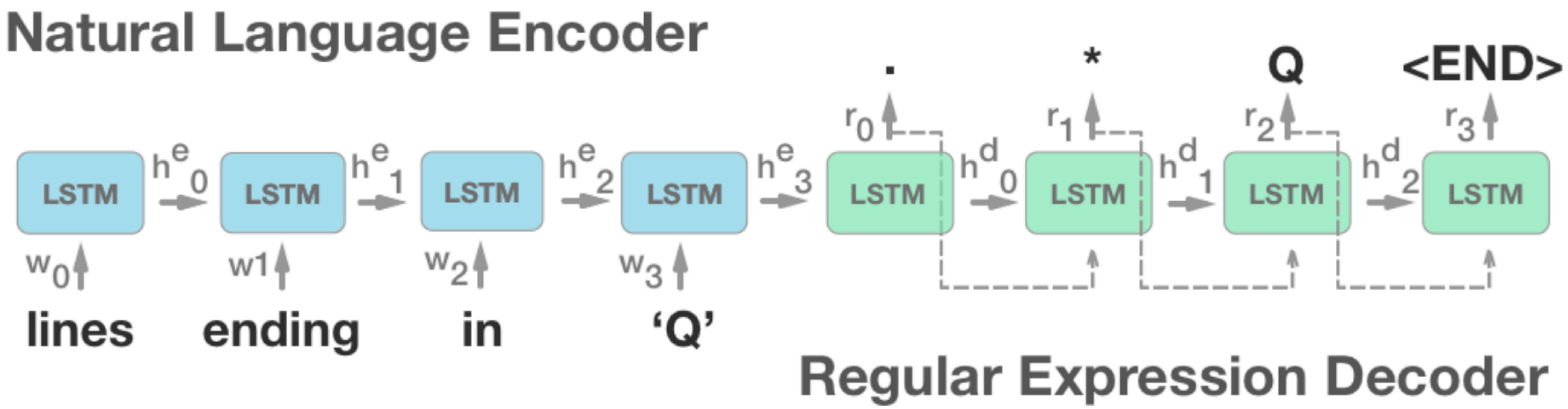
	GEO	ATIS
Previous Work		
Zettlemoyer and Collins (2007)		**84.6**
Kwiatkowski et al. (2010)	88.9	
Liang et al. (2011)[2]	91.1	
Kwiatkowski et al. (2011)	88.6	82.8
Poon (2013)		83.5
Zhao and Huang (2015)	88.9	84.2
Our Model		
No Recombination	85.0	76.3
ABSENTITIES	85.4	79.9
ABSWHOLEPHRASES	87.5	
CONCAT-2	84.6	79.0
CONCAT-3		77.5
AWP + AE	88.9	
AE + C2		78.8
AWP + AE + C2	**89.3**	
AE + C3		83.3

- Three forms of data augmentation all help
- Results on these tasks are still not as strong as hand-tuned systems from 10 years ago, but the same simple model can do well at all problems

Jia and Liang (2016)

Regex Prediction

- Predict regex from text



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

- Does not scale when regex specifications are more abstract (*I want to recognize a decimal number less than 20*)

Locascio et al. (2016)

SQL Generation

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

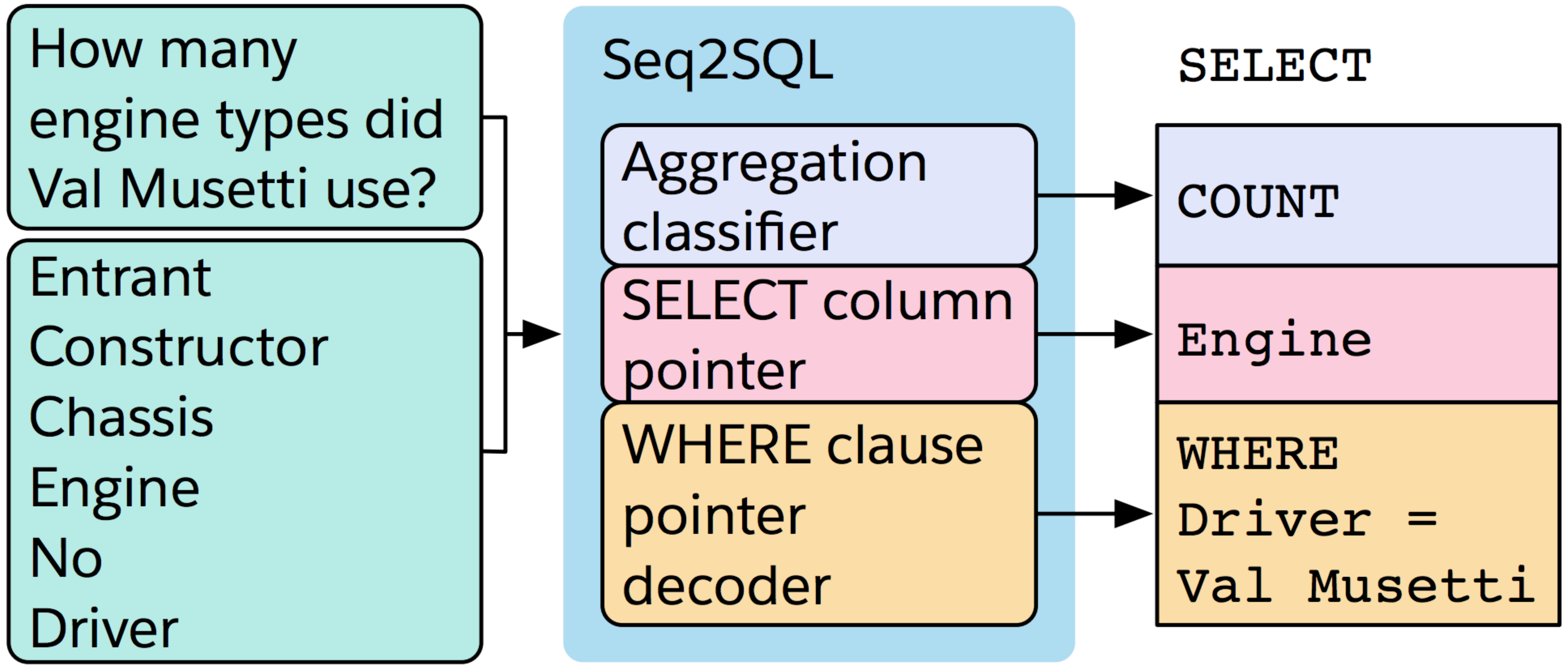
Question:

How many CFL teams are from York College?

SQL:

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

- How to ensure that well-formed SQL is generated?
  - Three seq2seq models
- How to capture column names + constants?
  - Pointer mechanisms, to be discussed later



Zhong et al. (2017)

Attention

"*what states border Texas*" ⟶ lambda x (state (x) and border (x , e89)))

- Orange pieces are probably reused across many problems
- Not too hard to learn to generate: start with lambda, always follow with x, follow that with paren, etc.
- LSTM has to remember the value of Texas for 13 steps!
- Next: attention mechanisms that let us "look back" at the input to avoid having to remember everything

Attention

Problems with Seq2seq Models

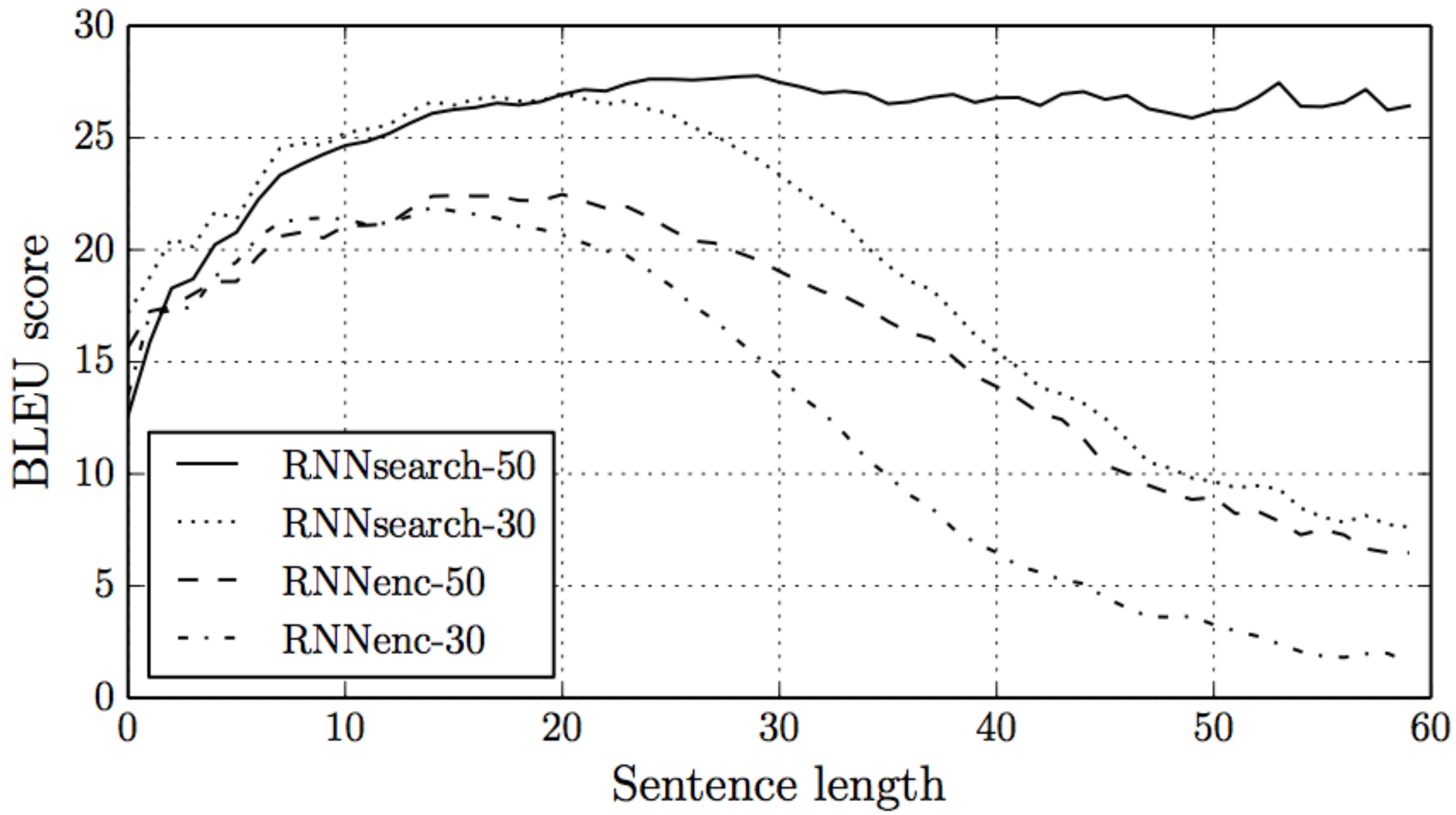
- Encoder-decoder models like to repeat themselves:

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

- Why does this happen?
  - Models trained poorly
  - Input is forgotten by the LSTM 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

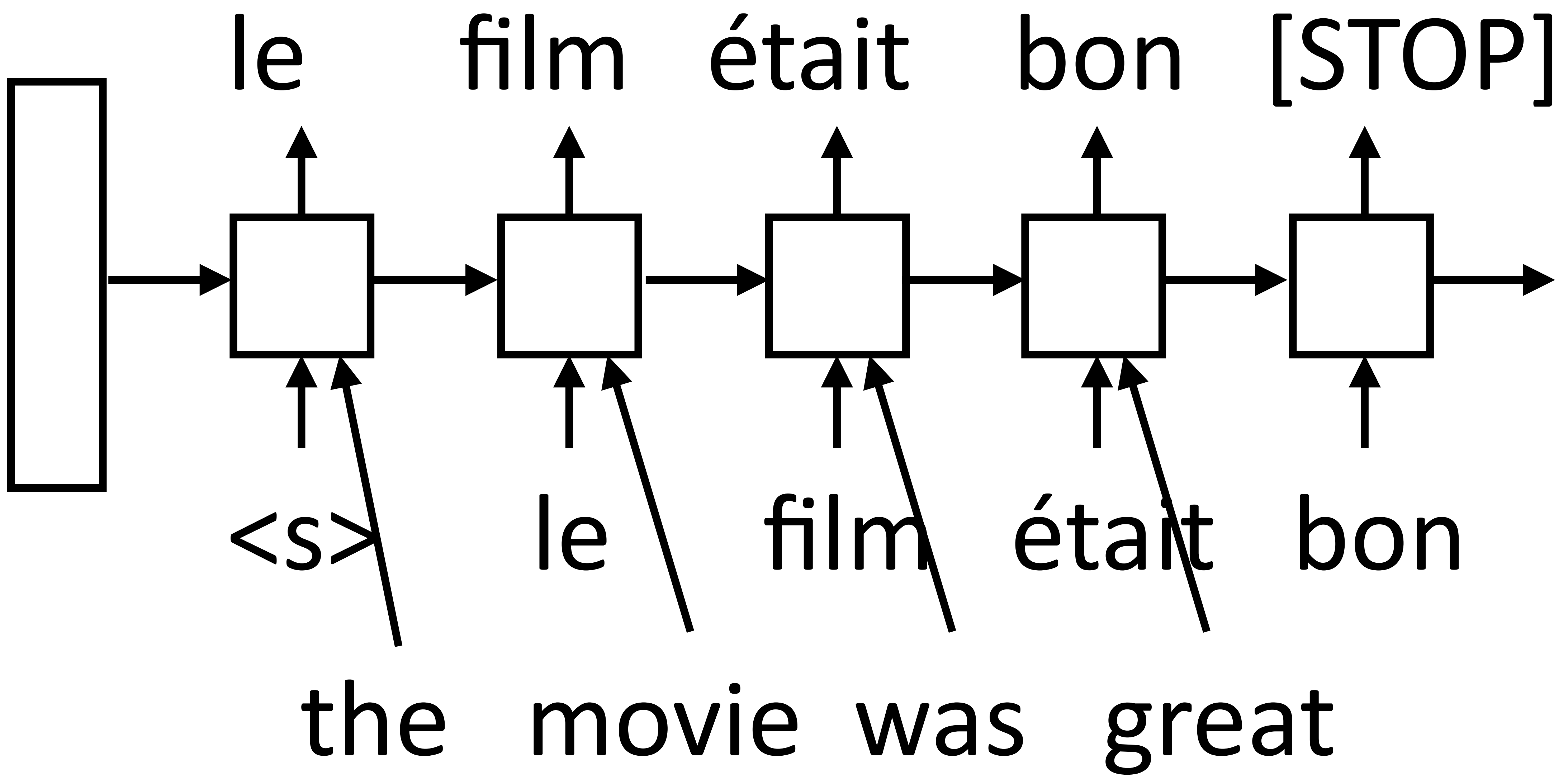
fr: Le *portique* *écotaxe* de *Pont-de-Buis* , . . . [truncated] . . . , a été *démonté* jeudi matin

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

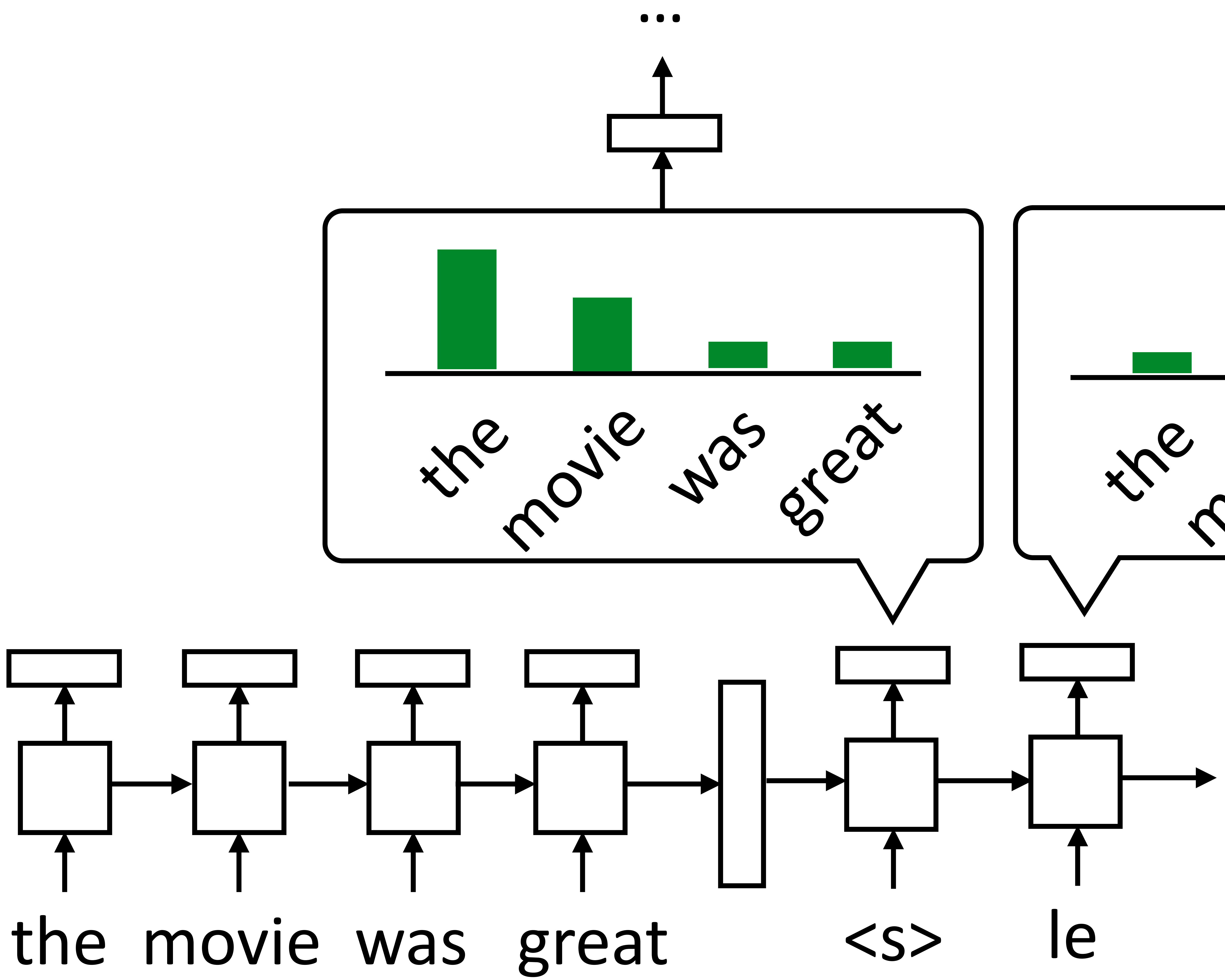
- Encoding these rare words into a vector space is really hard
- In fact, we don't want to encode them, we want a way of directly looking back at the input and copying them (Pont-de-Buis)

Aligned Inputs

- Suppose we knew the source and target would be word-by-word translated
- In that case, we could look at the corresponding input word when translating — might improve handling of long sentences!
- 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 the weighted sum of input tokens to predict output

Takeaways

- Rather than combining syntax and semantics like in CCG, we can either parse to semantic representations directly or generate them with seq2seq models

- Seq2seq models are a very flexible framework, some weaknesses can potentially be patched with more data

- How to fix their shortcomings? Next time: attention, copying, and transformers