THE OHIO STATE UNIVERSITY

CSE 5525: Foundations of Speech and Language Processing

Sequence to sequence (seq2seq)

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Many thanks to Prof. Greg Durrett @ UT Austin for sharing his slides.

This Lecture

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

Encoder-Decoder Models

Encoder-Decoder

Input: sequence A
Output: sequence B

- Semantic parsing:

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

- Syntactic parsing

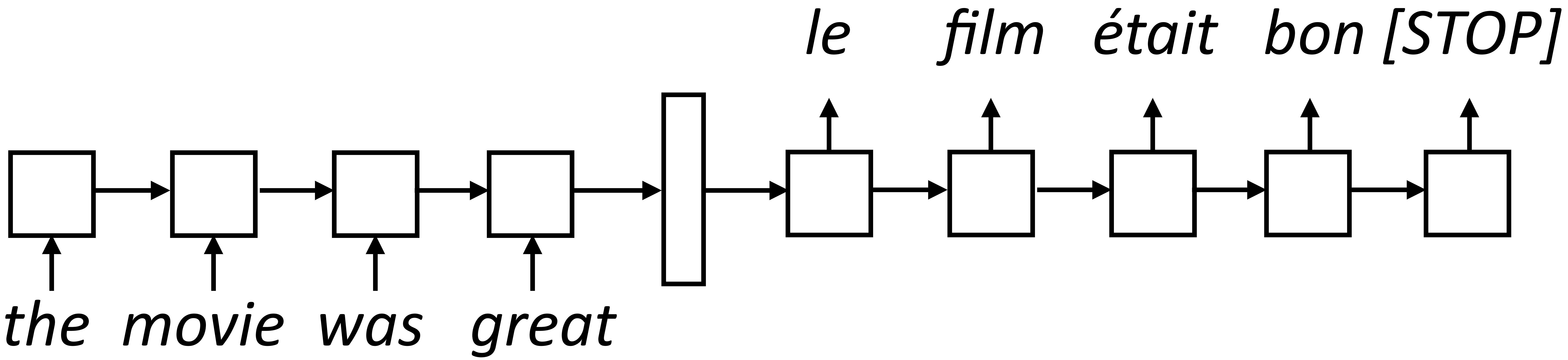
The dog ran → `(S (NP (DT the) (NN dog) ) (VP (VBD ran) ) )`

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

- Machine translation (e.g., English sentence as input and French as output), summarization, dialogue can all be viewed in this framework as well

Encoder-Decoder

- Encode a sequence into a fixed-sized vector



En -> Fr translation

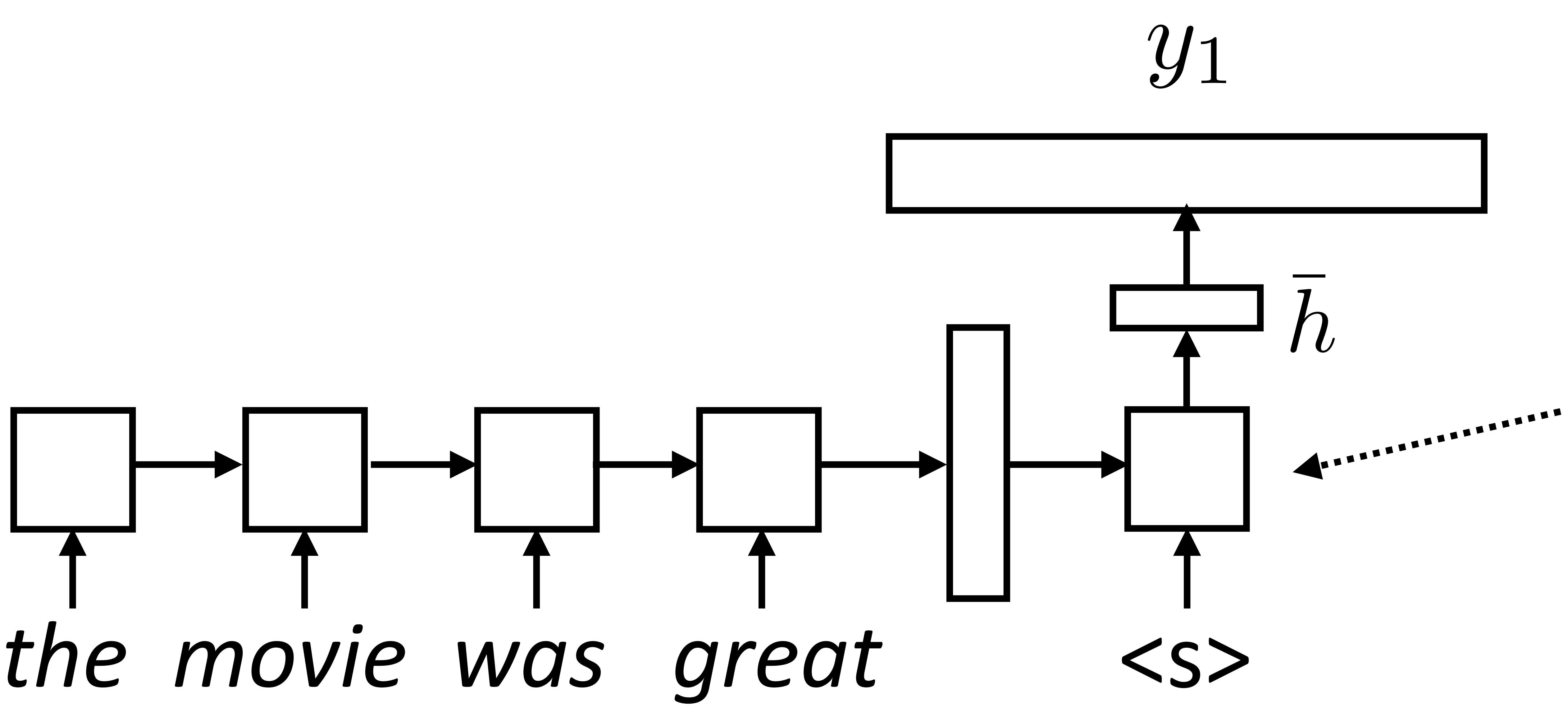
- Now use that vector to produce a series of tokens as output from a separate LSTM *decoder*

Sutskever et al. (2014)

Model

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

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



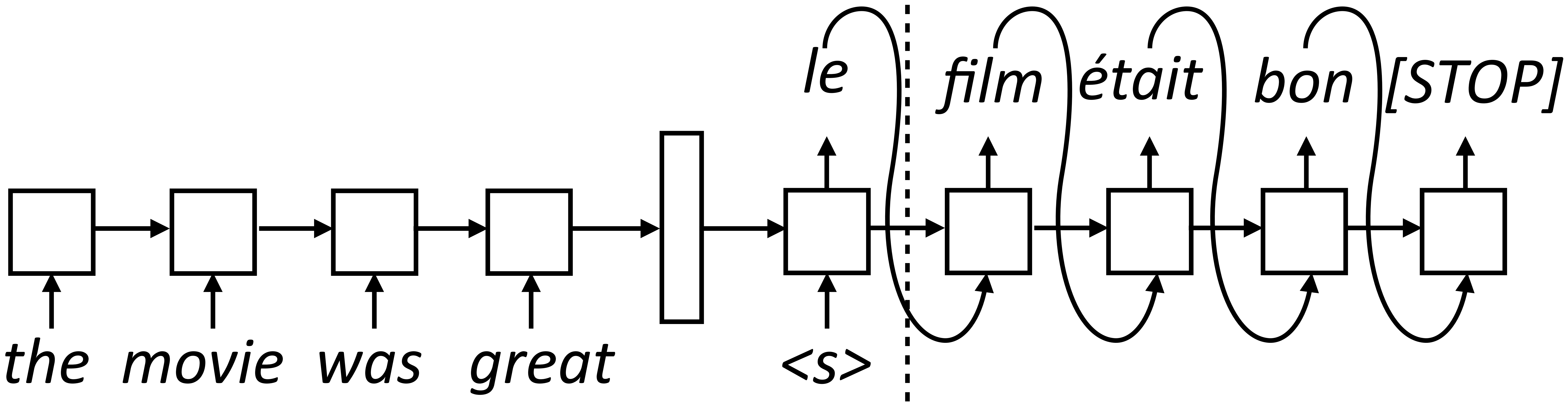
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \mathrm{softmax}(W\bar{h})$$

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

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

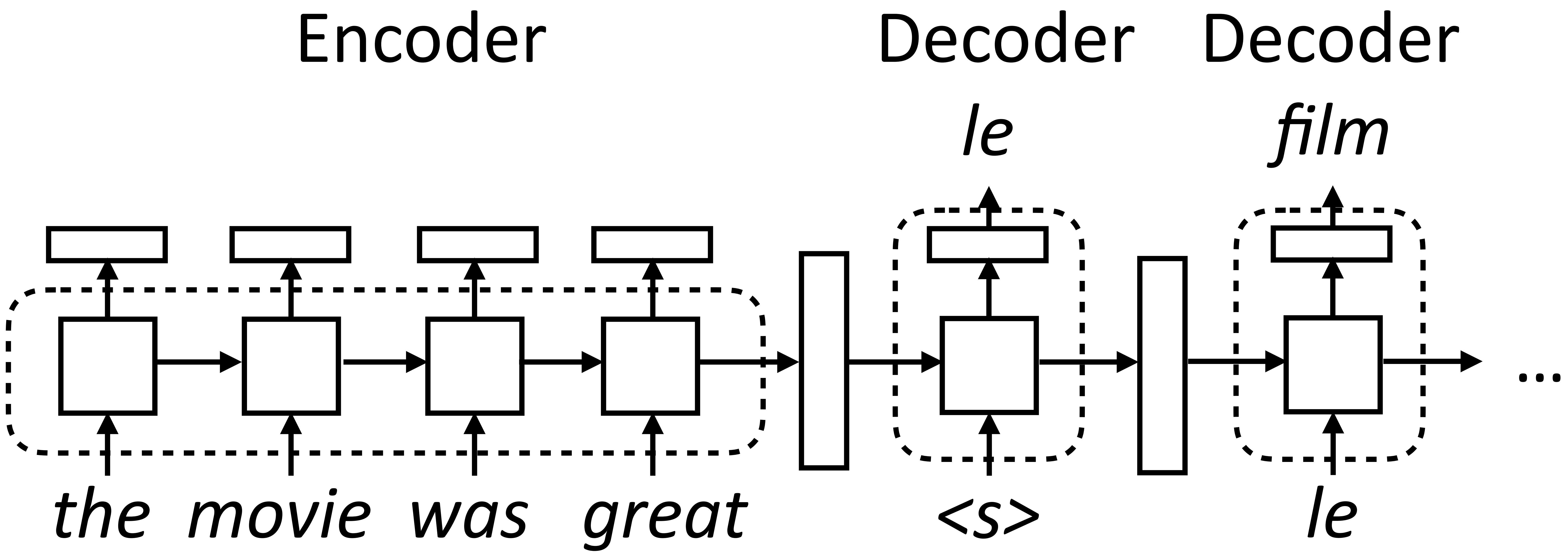
Inference

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



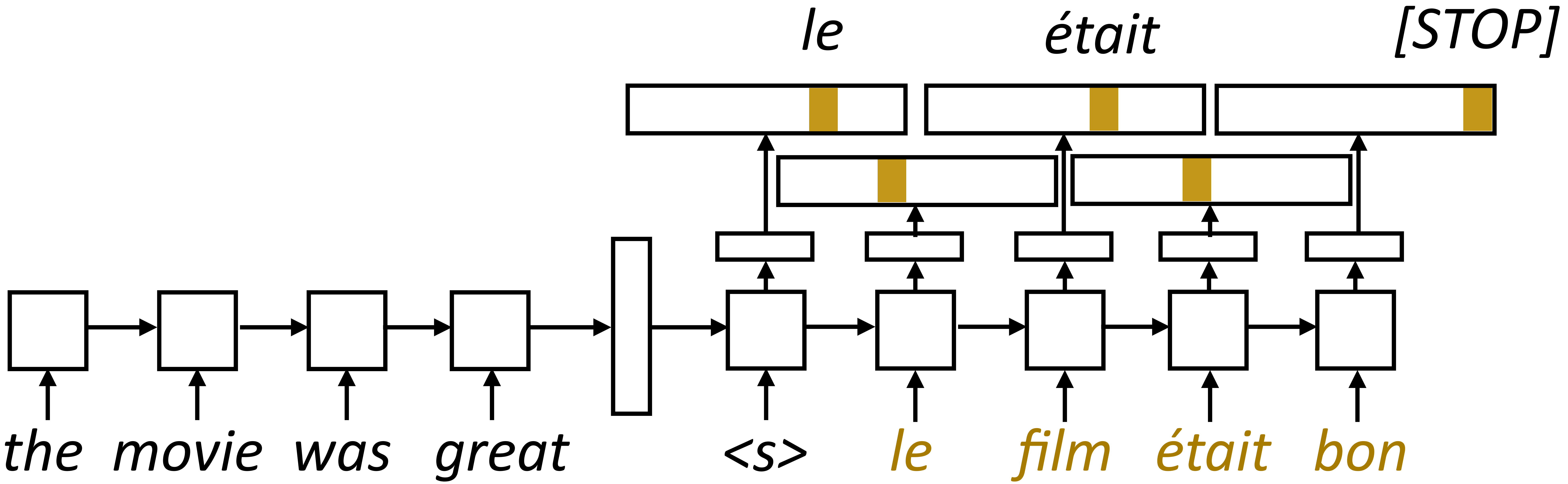
- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

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

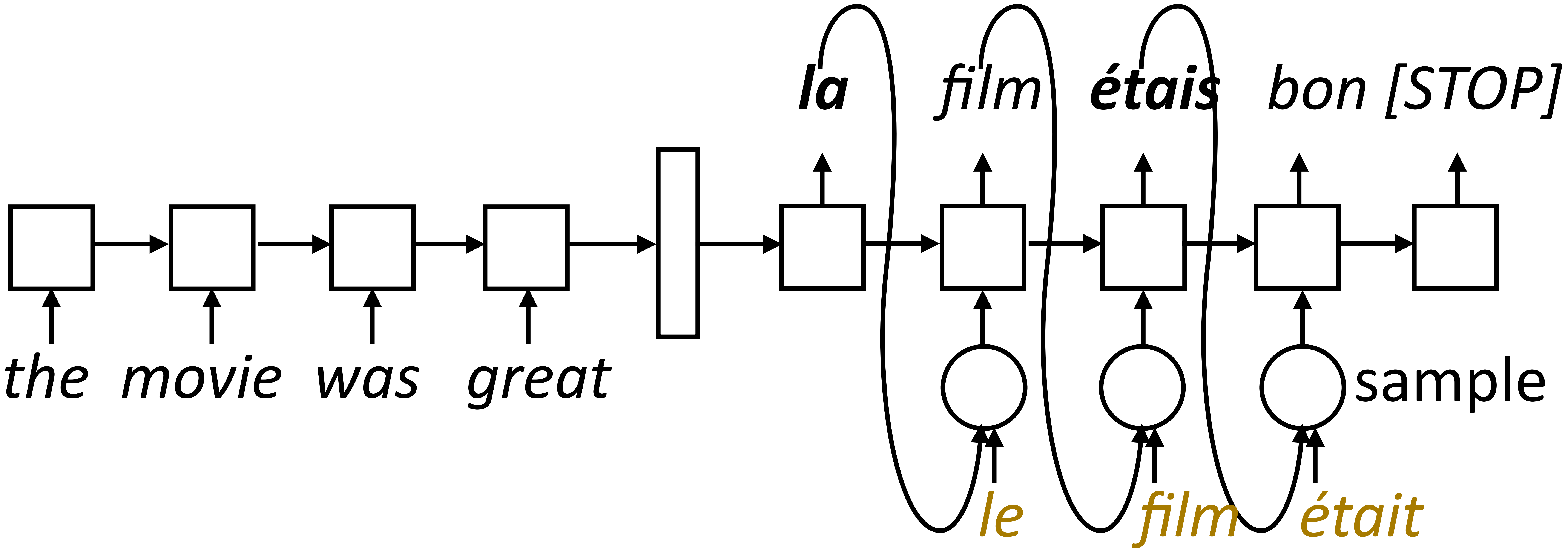


- Objective: maximize $\sum_{(\mathbf{x},\mathbf{y})} \sum_{i=1}^{n} \log P(y_i^* | \mathbf{x}, y_1^*, \ldots, y_{i-1}^*)$

- 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: Check out HW3 encoder
- 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

Offline reading & practice in HW3

Implementation Details (cont'd)

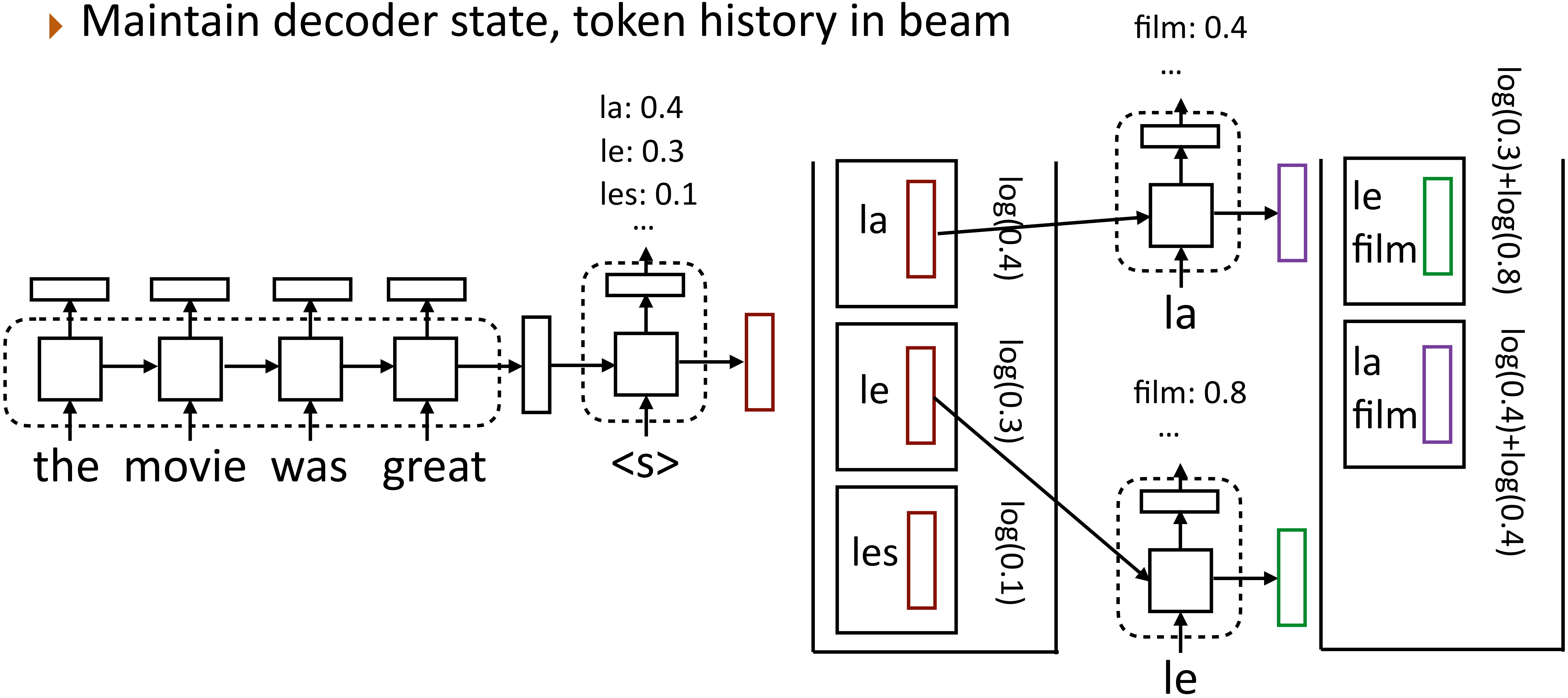
- Batching is pretty tricky: decoder is across time steps, so you probably want your label vectors to look like [num timesteps x batch size x num labels], iterate upwards by time steps

- Beam search: can help with lookahead. Finds the (approximate) highest scoring sequence:

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

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: Convolutional Neural Networks (CNN) encoders, decoders can be any autoregressive model including certain types of CNNs
- Transformer: another widely used model recently developed: https://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf

Offline reading & practice in HW3

Seq2seq Semantic Parsing

Semantic Parsing as Translation

"what states border Texas" Question

↓

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

- 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)

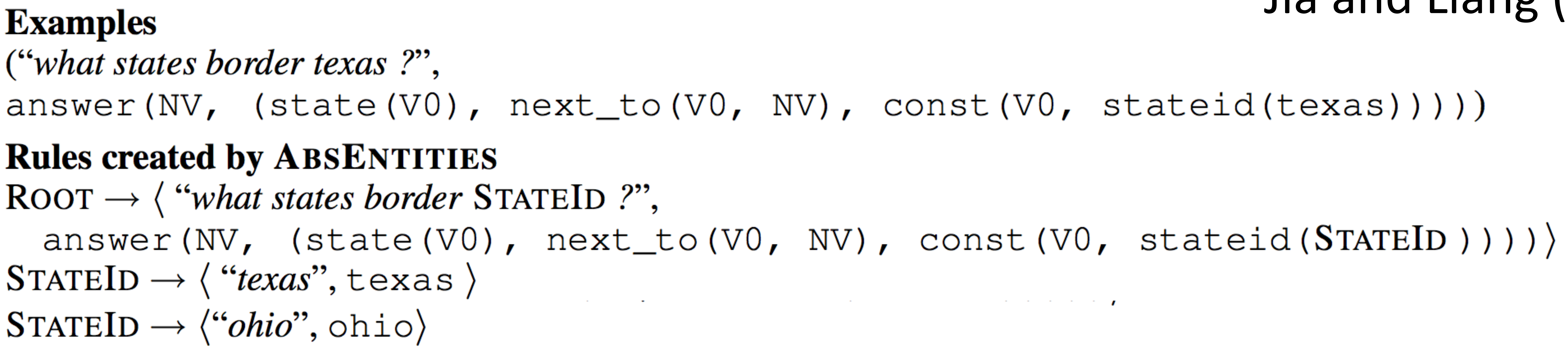
Handling Invariances

“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

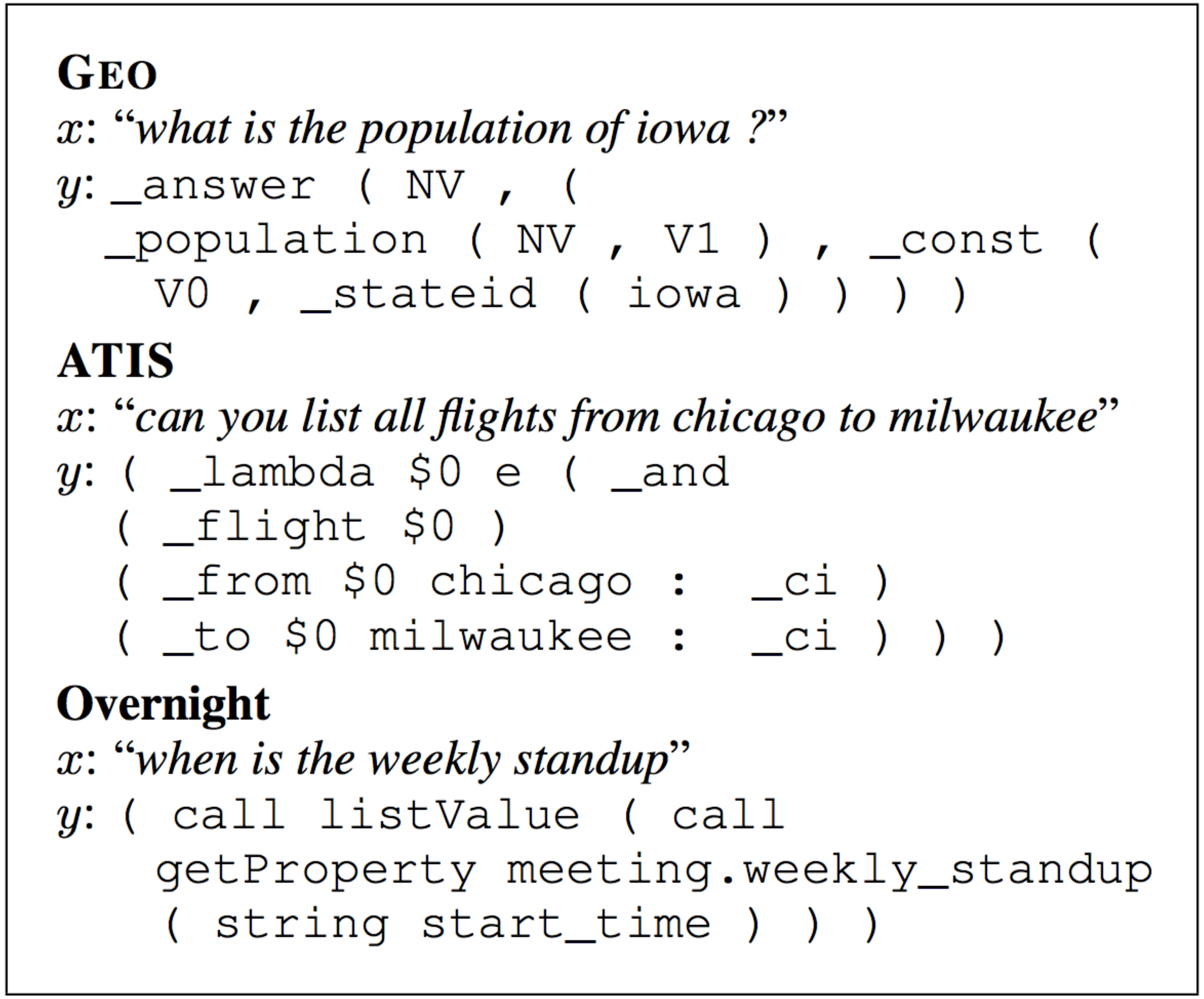
(“*what states border texas ?*”,
`answer(NV, (state(V0), next_to(V0, NV), const(V0, stateid(texas))))`

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*"

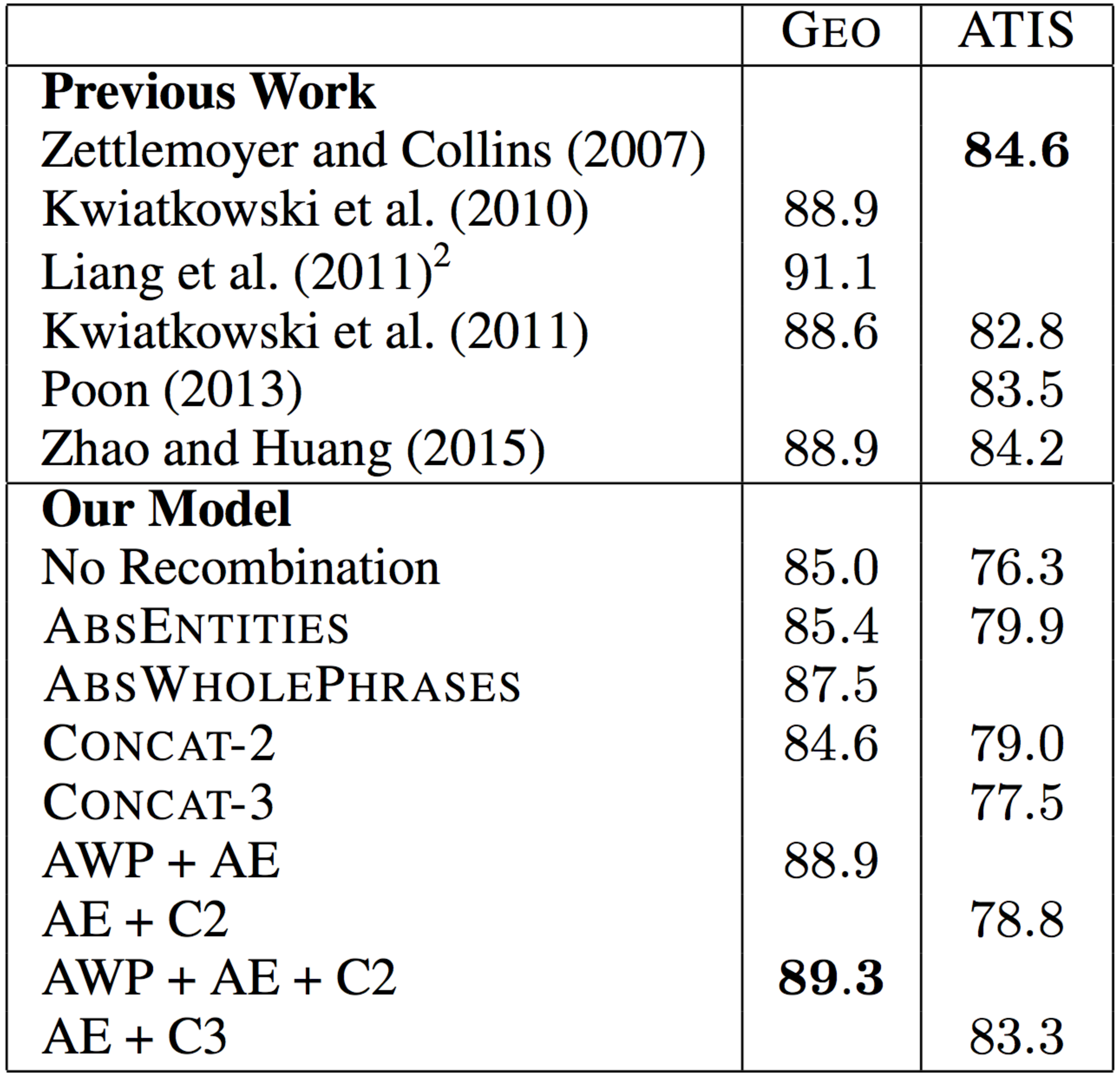
y:
```
( call listValue ( call
  getProperty meeting.weekly_standup
  ( string start_time ) ) )
```

- 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

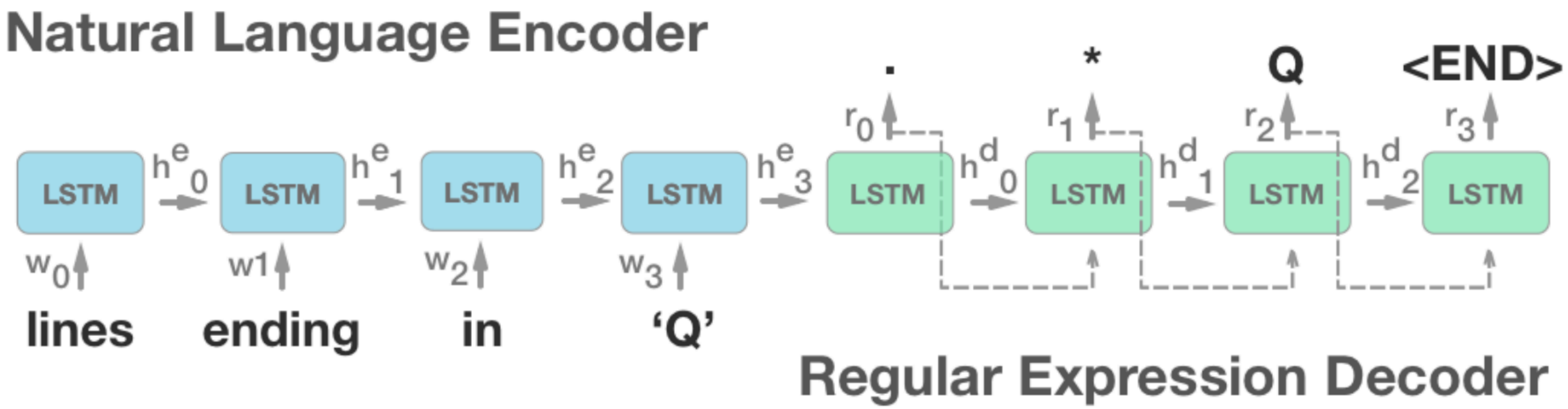
- Three forms of data augmentation all help

- 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

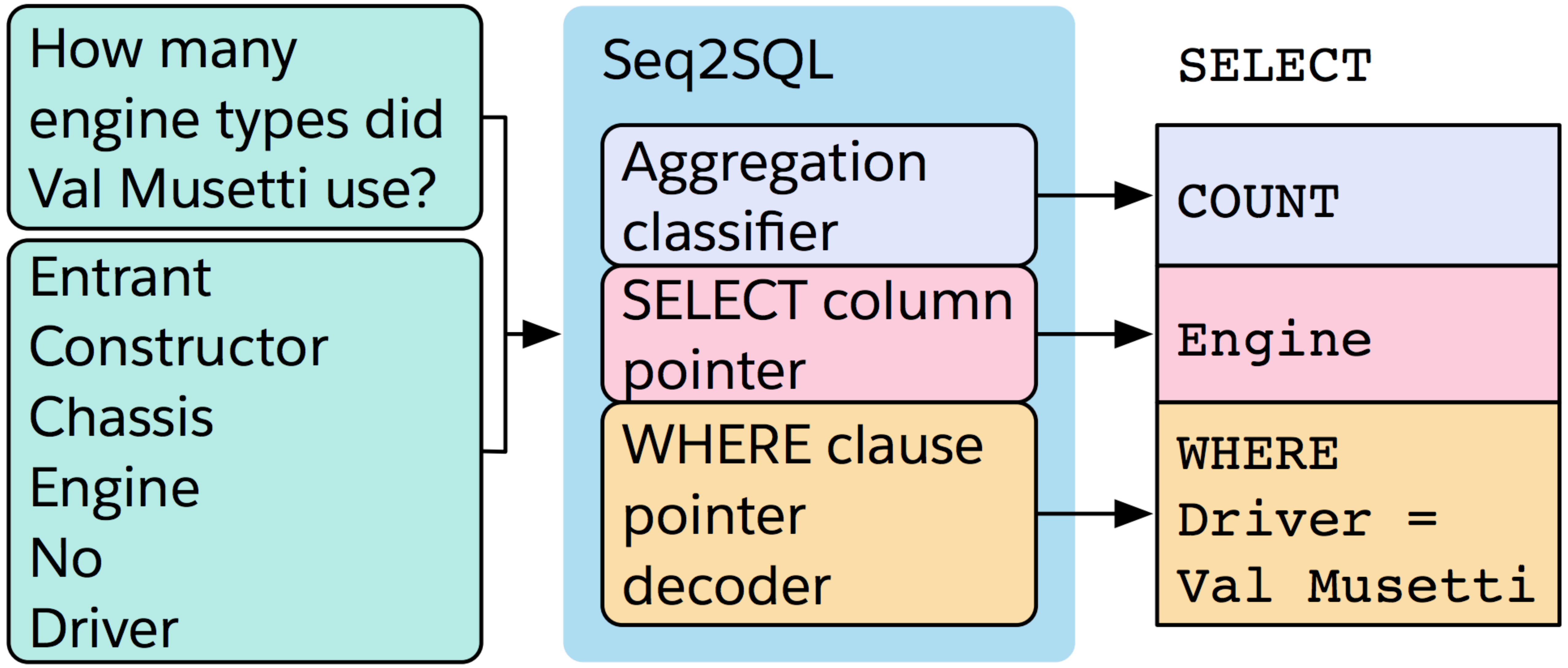
- Convert natural language description into a SQL query against some DB
- How to ensure that well-formed SQL is generated?
  - Three seq2seq models
- How to capture column names + constants?
  - Pointer mechanisms, to be discussed later

Question:

How many CFL teams are from York College?

SQL:

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



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

Takeaways

- How encoder-decoder models work

- Seq2seq models are a very flexible framework for various problems. Some weaknesses can potentially be patched with more data

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