CS388: Natural Language Processing
Lecture 14: Semantics II / Seq2seq I

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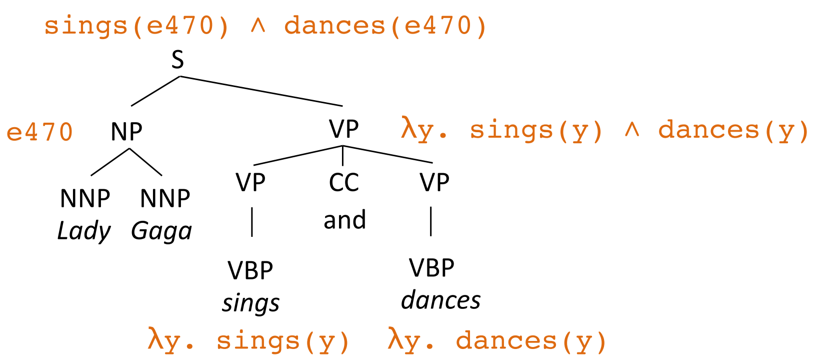
Administrivia

- Graham Neubig (CMU) talk this Friday at 11am in 6.302.
  "Towards Open-domain Generation of Programs from Natural Language"
- Mini 2 graded by the end of the week
- Project 2 out by Thursday

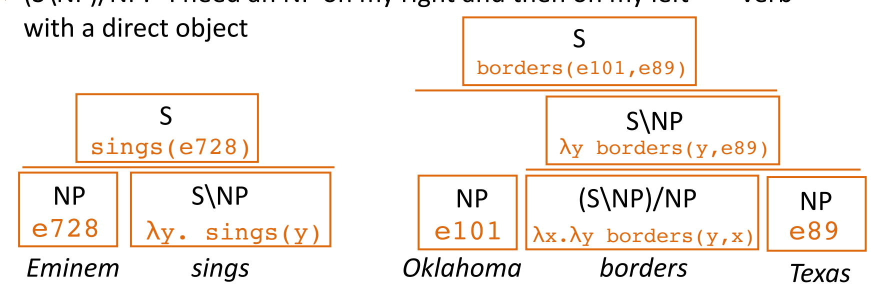
Recall: Parses to Logical Forms



- General rules: VP: λy. a(y) ∧ b(y) -> VP: λy. a(y) CC VP: λy. 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



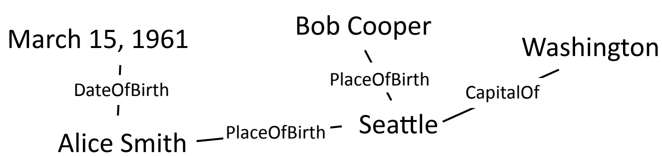
This Lecture

- Lambda-DCS: more lightweight than CCG
- Seq2seq models
- Seq2seq models for semantic parsing

Lambda-DCS

Lambda-DCS

- Dependency-based compositional semantics — original version was less powerful than lambda calculus, lambda-DCS is as powerful
- Designed in the context of building a QA system from Freebase
- Freebase: set of entities and relations



- [[PlaceOfBirth]] = set of pairs of (person, location)

Liang et al. (2011), Liang (2013)

Lambda-DCS

Lambda-DCS	Lambda calculus
`Seattle`	$\lambda x.\ x = \texttt{Seattle}$
`PlaceOfBirth`	$\lambda x.\lambda y.\ \texttt{PlaceOfBirth}(x,y)$
`PlaceOfBirth.Seattle`	$\lambda x.\ \texttt{PlaceOfBirth}(x,\texttt{Seattle})$

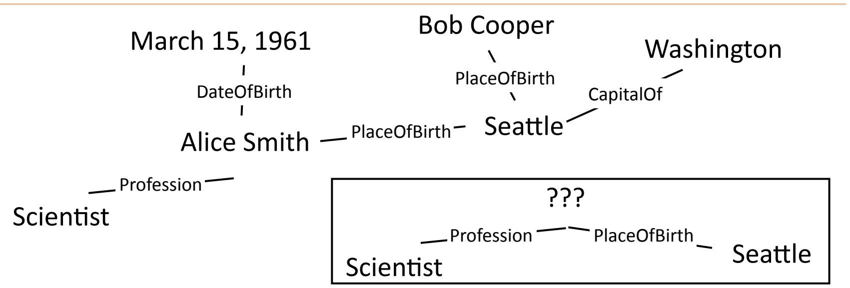
- Looks like a tree fragment over Freebase, denotes the set of people born in Seattle, no explicit variables

??? — PlaceOfBirth — Seattle

`Profession.Scientist` $\wedge$ `PlaceOfBirth.Seattle`	$\lambda x.\ \texttt{Profession}(x,\texttt{Scientist}) \wedge \texttt{PlaceOfBirth}(x,\texttt{Seattle})$

Liang et al. (2011), Liang (2013)

Lambda-DCS



"list of scientists born in Seattle"

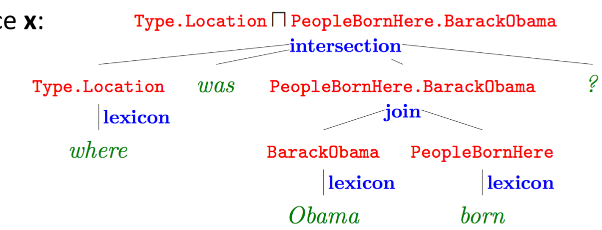
`Profession.Scientist ∧ PlaceOfBirth.Seattle`

- Execute this fragment against Freebase, returns Alice Smith (and others)

Liang et al. (2011), Liang (2013)

Parsing into Lambda-DCS

- Derivation **d** on sentence **x**:



- No more explicit syntax in these derivations like we had in CCG
- Everything is a set, sets combine in a few ways
- Building the lexicon: more sophisticated process than GENLEX, but can handle thousands of predicates
- Log-linear model with features on rules: $P(\mathbf{d}|\mathbf{x}) \propto \exp w^\top \left(\sum_{r \in \mathbf{d}} f(r, \mathbf{x})\right)$

Berant et al. (2013)

Parsing into Lambda-DCS

- Learn from derivations: standard supervised learning, maximize probability of correct derivation

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} \log P(\mathbf{d}_i^*|\mathbf{x}_i)$$

- Problem: supervision looks like "Where was Barack Obama born" — "Hawaii" without a derivation

Berant et al. (2013)

Parsing into Lambda-DCS

- Learn just from question-answer pairs: maximize the likelihood of the right denotation *y** with the derivation **d** marginalized out

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} \log \sum_{\mathbf{d}:[[\mathbf{d}]]_{\mathcal{K}}=y_i^*} P(\mathbf{d}|\mathbf{x}_i)$$

sum over derivations **d** such that the denotation of **d** on knowledge base *K* is y_i

Approx procedure: for each example:

Run beam search to get a set of derivations

Let d = highest-scoring derivation in the beam

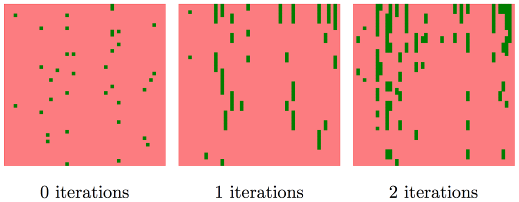
Let d* = highest-scoring derivation in the beam *with correct denotation*

Do a structured perceptron update towards d* away from d

Berant et al. (2013)

Learning

- Each vertical slice is the beam for one example. Green = correct denotation



- Only a small number of questions are even reachable by beam search initially (but some questions are very easy so even a totally untrained model can answer them)
- During training, more and more "good" derivations surface and will result in model updates

Berant et al. (2013)

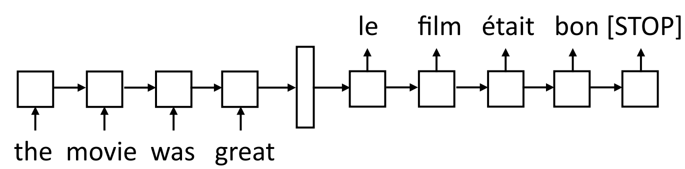
Encoder-Decoder Models

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
- Encoder-decoder models can be a lot more uniform — we'll come back to this later in the lecture

Encoder-Decoder

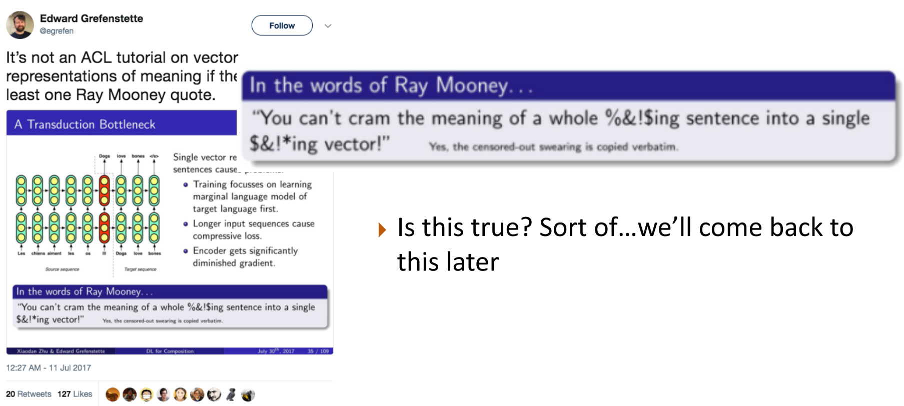
- Encode a sequence into a fixed-sized vector



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

Sutskever et al. (2014)

Encoder-Decoder



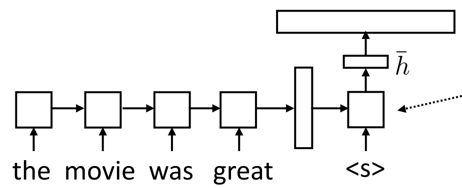
- Is this true? Sort of…we'll come back to this later

Model

- Generate next word conditioned on previous word as well as hidden state
- W size is |vocab| x |hidden state|, softmax over entire vocabulary

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

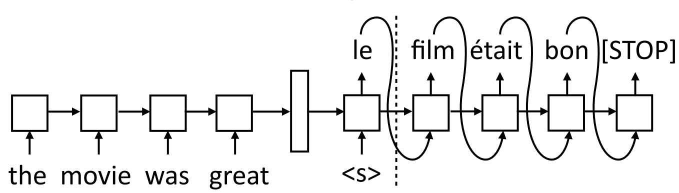
$$P(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{n} P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1})$$



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

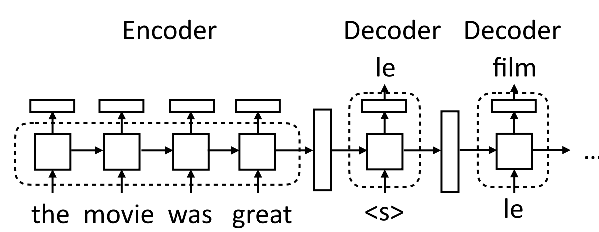
Inference

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



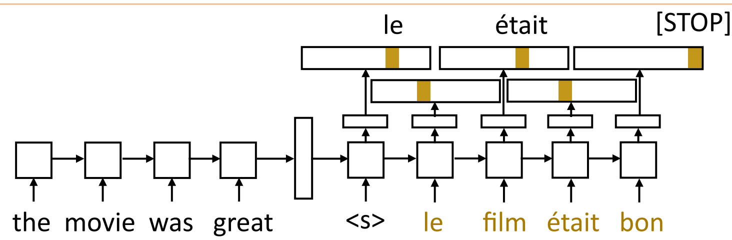
- During inference: need to compute the argmax over the word predictions and then feed that to the next RNN state
- Need to actually evaluate computation graph up to this point to form input for the next state
- Decoder is advanced one state at a time until [STOP] is reached

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

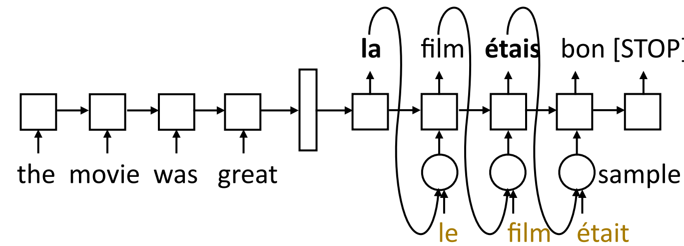
Training



- 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

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 and use a mask or indexing to access a subset of terms
- Encoder: looks like what you did in Mini 2. Can be a CNN/LSTM/…
- Decoder: also flexible in terms of architecture (more next lecture). 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

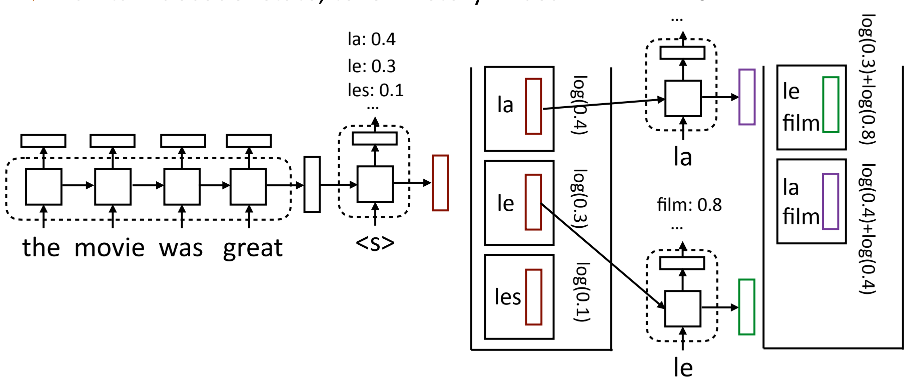
Implementation Details (cont'd)

- 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



- Do **not** max over the two *film* states! Hidden state vectors are different

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 (2015)

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

Examples

Jia and Liang (2015)

```
("what states border texas ?",
answer(NV, (state(V0), next_to(V0, NV), const(V0, stateid(texas)))))
("what is the highest mountain in ohio ?",
answer(NV, highest(V0, (mountain(V0), loc(V0, NV), const(V0, stateid(ohio))))))
```

Rules created by AbsEntities

```
Root → ⟨ "what states border StateId ?",
  answer(NV, (state(V0), next_to(V0, NV), const(V0, stateid(StateId)))))⟩
StateId → ⟨ "texas", texas ⟩
Root → ⟨ "what is the highest mountain in StateId ?",
  answer(NV, highest(V0, (mountain(V0), loc(V0, NV),
                  const(V0, stateid(StateId))))))⟩
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 (2015)

Semantic Parsing as Translation

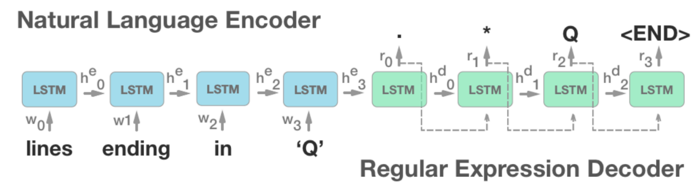
	Geo	ATIS
Previous Work		
Zettlemoyer and Collins (2007)		**84.6**
Kwiatkowski et al. (2010)	88.9	
Liang et al. (2011)[2]	91.1	
Kwiatkowski et al. (2011)	88.6	82.8
Poon (2013)		83.5
Zhao and Huang (2015)	88.9	84.2
Our Model		
No Recombination	85.0	76.3
AbsEntities	85.4	79.9
AbsWholePhrases	87.5	
Concat-2	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 (2015)

Regex Prediction

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

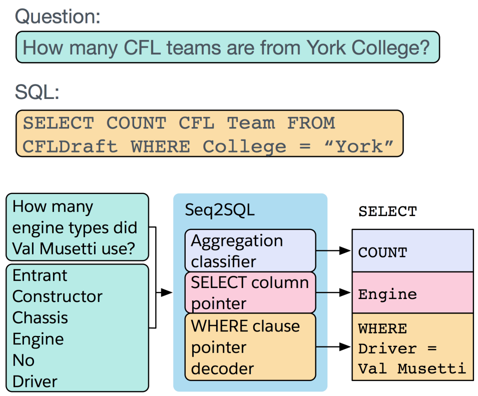


- Problem: requires a lot of data: 10,000 examples needed to get ~60% accuracy on pretty simple regexes

Locascio et al. (2016)

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



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. This is a common question
- LSTM has to remember the value of Texas for 13 steps!
- Next lecture: attention mechanisms that let us "look back" at the input to avoid having to remember everything

Takeaways

- Lambda-DCS is a more lightweight formalism than lambda calculus
- 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