CS388: Natural Language Processing

Lecture 14: Semantics / Seq2seq I

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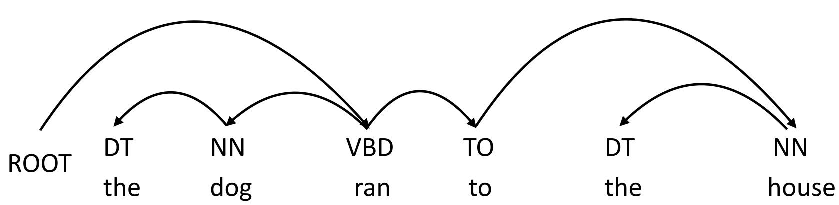
Administrivia

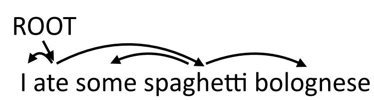
- Final project proposals due Thursday; can exceed 1 page if needed
- P2 released Thursday, due three weeks after

Recall: Dependencies

- Dependency syntax: syntactic structure is defined by dependencies
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol
  - Dependencies must form a directed acyclic graph



Recall: Shift-Reduce Parsing



- State: Stack: [ROOT I ate] Buffer: [some spaghetti bolognese]
- Left-arc (reduce operation): Let σ denote the stack
  - "Pop two elements, add an arc, put them back on the stack"

  $\boxed{\sigma | w_{-2}, w_{-1}} \rightarrow \boxed{\sigma | w_{-1}}$, w_{-2} is now a child of w_{-1}
- Train a classifier to make (shift, left-arc, right-arc) decisions sequentially — that classifier can parse sentences for you

Where are we now?

- Classification, then sequences, then trees
- Now we can understand sentences in terms of tree structures as well
- Why is this useful? What does this allow us to do?
- We're going to see how parsing can be a stepping stone towards more formal representations of language meaning. We'll contrast with these approaches when we revisit the same problems later with neural nets.

Today

- Montague semantics:
  - Model theoretic semantics
  - Compositional semantics with first-order logic
- CCG parsing for database queries
- Seq2seq semantic parsing

Model Theoretic Semantics

Model Theoretic Semantics

- Key idea: can ground out natural language expressions in set-theoretic expressions called *models* of those sentences
- Natural language statement S => interpretation of S that models it

  She likes going to that restaurant

  - Interpretation: defines who *she* and *that restaurant* are, make it able to be concretely evaluated with respect to a *world*
- Entailment (statement A implies statement B) reduces to: in all worlds where A is true, B is true
- Our modeling language is *first-order logic*

First-order Logic

- Powerful logic formalism including things like entities, relations, and quantifications

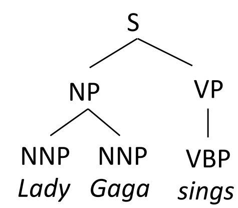
Lady Gaga sings

- sings is a *predicate* (with one argument), function f: entity → true/false
- sings(Lady Gaga) = true or false, have to execute this against some database (*world*)
- Quantification: "forall" operator, "there exists" operator

$\forall x$ sings(x) $\vee$ dances(x) → performs(x)

"Everyone who sings or dances performs"

Montague Semantics



Id	Name	Alias	Birthdate	Sings?
e470	Stefani Germanotta	Lady Gaga	3/28/1986	T
e728	Marshall Mathers	Eminem	10/17/1972	T

Database containing entities, predicates, etc.

- Sentence expresses something about the world which is either true or false
- Denotation: evaluation of some expression against this database

`[[`*Lady Gaga*`]] = e470` — denotation of this string is an entity

`[[sings(e470)]] = True` — denotation of this expression is T/F

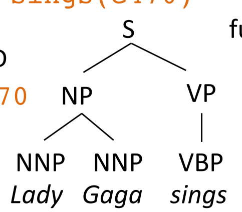
Montague Semantics

`sings(e470)`

function application: apply this to e470

ID

`e470`



`λy. sings(y)` (VP)

`λy. sings(y)` (sings)

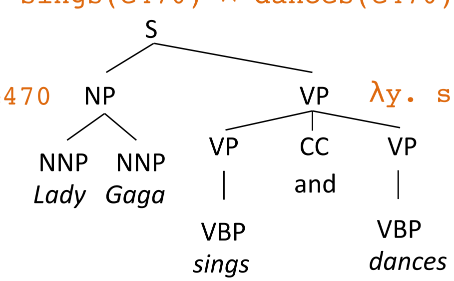
takes one argument (y, the entity) and returns a logical form `sings(y)`

- We can use the syntactic parse as a bridge to the lambda-calculus representation, build up a logical form (our model) *compositionally*

Parses to Logical Forms

`sings(e470) ∧ dances(e470)`

`e470`

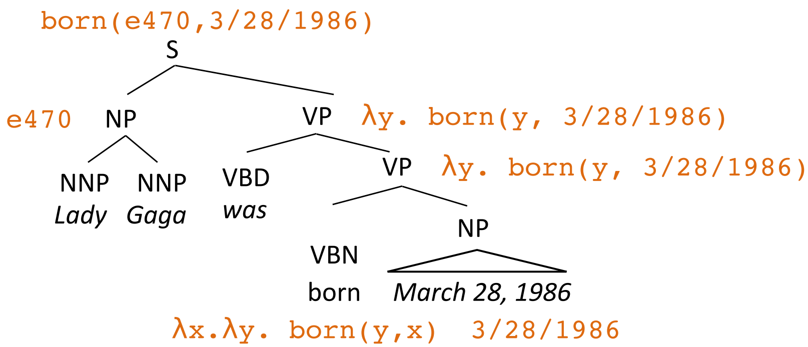


`λy. sings(y) ∧ dances(y)`

`λy. sings(y)` `λy. dances(y)`

- General rules: VP: λy. a(y) ∧ b(y) -> VP: λy. a(y) CC VP: λy. b(y)
  S: f(x) -> NP: x VP: f

Parses to Logical Forms



- Function takes two arguments: first x (date), then y (entity)
- How to handle tense: should we indicate that this happened in the past?

Tricky things

- Adverbs/temporality: *Lady Gaga sang well yesterday*

  `sings(Lady Gaga, time=yesterday, manner=well)`

  - "Neo-Davidsonian" view of events: things with many properties:

    $\exists e.\ \mathtt{type(e,sing)} \wedge \mathtt{agent(e,e470)} \wedge \mathtt{manner(e,well)} \wedge \mathtt{time(e,\ldots)}$

- Quantification: *Everyone is friends with someone*

  $\exists y\ \forall x\ \mathtt{friend(x,y)}$ (one friend) $\forall x\ \exists y\ \mathtt{friend(x,y)}$ (different friends)

  - Same syntactic parse for both! So syntax doesn't resolve all ambiguities

- Indefinite: *Amy ate a waffle* $\exists w.\ \mathtt{waffle(w)} \wedge \mathtt{ate(Amy,w)}$
- Generic: *Cats eat mice* (all cats eat mice? most cats? some cats?)

Semantic Parsing

- For question answering, syntactic parsing doesn't tell you everything you want to know, but indicates the right structure

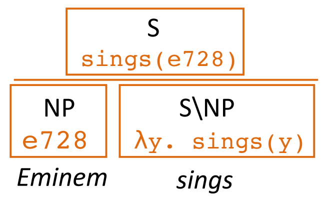
- Solution: *semantic parsing*: many forms of this task depending on semantic formalisms

- CCG parsers can produce these kinds of expressions, which can be used for database querying/question answering

CCG Parsing

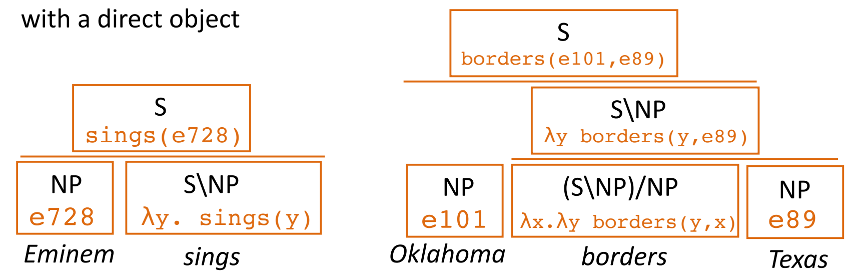
Combinatory Categorial Grammar

- Steedman+Szabolcsi (1980s): formalism bridging syntax and semantics
- Parallel derivations of syntactic parse and lambda calculus expression
- 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
- When you apply this, there has to be a parallel instance of function application on the semantics side



Combinatory Categorial Grammar

- 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



CCG Parsing

What	states	border	Texas
$(S/(S\backslash NP))/N$ $\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)$	N $\lambda x.state(x)$	$(S\backslash NP)/NP$ $\lambda x.\lambda y.borders(y,x)$	NP $texas$

$$\xrightarrow{\quad} \; (S\backslash NP) \quad \lambda y.borders(y, texas)$$

- "What" is a ***very*** complex type: needs a noun and needs a S\NP to form a sentence. S\NP is basically a verb phrase (*border Texas*)

Zettlemoyer and Collins (2005)

CCG Parsing

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$$S/(S\backslash NP) \quad \lambda g.\lambda x.state(x) \wedge g(x) \qquad (S\backslash NP) \quad \lambda y.borders(y, texas)$$

$$S \quad \lambda x.state(x) \wedge borders(x, texas)$$

- "What" is a ***very*** complex type: needs a noun and needs a S\NP to form a sentence. S\NP is basically a verb phrase (*border Texas*)
- Lexicon is highly ambiguous — all the challenge of CCG parsing is in picking the right lexicon entries

Zettlemoyer and Collins (2005)

CCG Parsing

Show me	flights	to	Prague
S/N $\lambda f.f$	N $\lambda x.flight(x)$	(N\N)/NP $\lambda y.\lambda f.\lambda x.f(x) \wedge to(x,y)$	NP PRG

N\N
$\lambda f.\lambda x.f(x) \wedge to(x,PRG)$

N
$\lambda x.flight(x) \wedge to(x,PRG)$

S
$\lambda x.flight(x) \wedge to(x,PRG)$

- "to" needs an NP (destination) and N (parent)

Slide credit: Dan Klein

Building CCG Parsers

- Training data looks like pairs of sentences and logical forms

What states border Texas λx. state(x) ∧ borders(x, e89)

- Problem: we don't know the derivation
  - *Texas* corresponds to NP | e89 in the logical form (easy to figure out)
  - *What* corresponds to (S/(S\NP))/N | λf.λg.λx. f(x) ∧ g(x)
  - How do we infer that without being told it?
- Building these parsers is very hard…let's try a different approach!

Zettlemoyer and Collins (2005)

Encoder-Decoder Models

Encoder-Decoder

- Can view many tasks as mapping from an input sequence of tokens to an output sequence of tokens
- Semantic parsing:

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

- Syntactic parsing

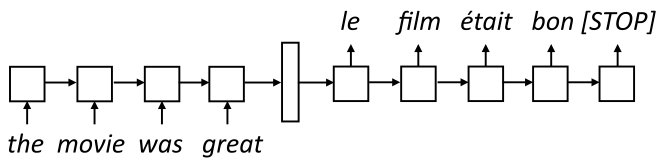
The dog ran ⟶ (S (NP (DT the) (NN dog)) (VP (VBD ran)))

(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 — our examples will be MT for now

Encoder-Decoder

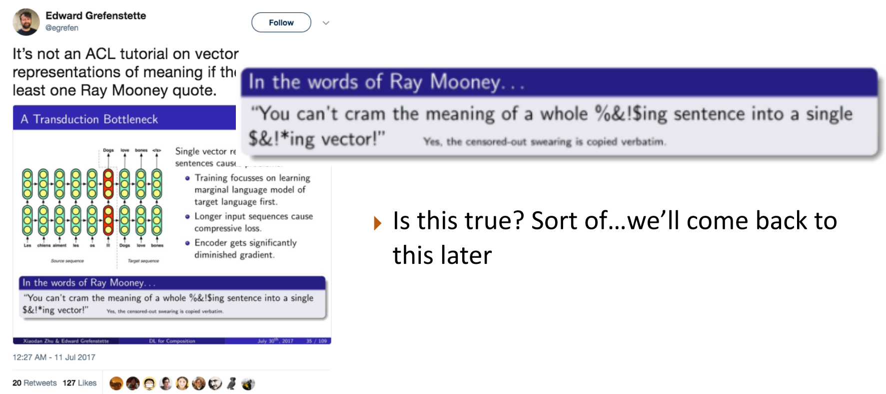
- Encode a sequence into a fixed-sized vector



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

Sutskever et al. (2014)

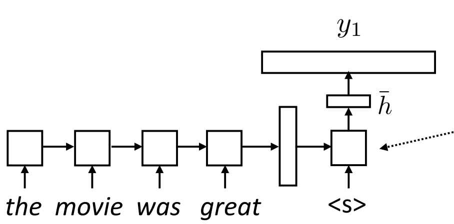
Encoder-Decoder



- 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



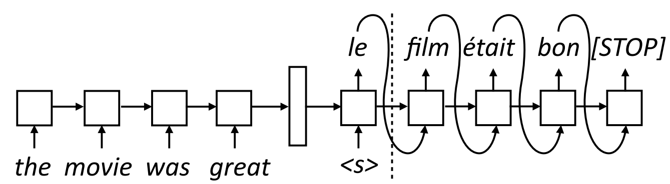
$$P(y_i|\mathbf{x}, y_1, \ldots, y_{i-1}) = \text{softmax}(W\bar{h})$$

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

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

Inference

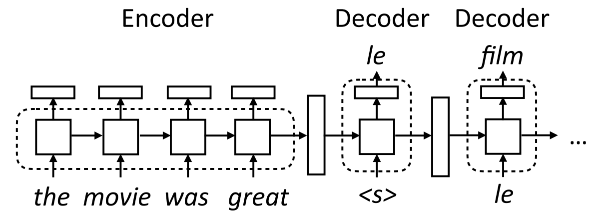
- Generate next word conditioned on previous word as well as hidden state



- 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

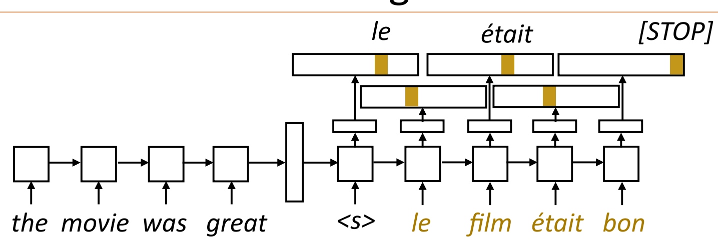
Implementing Encoder-Decoder Models

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

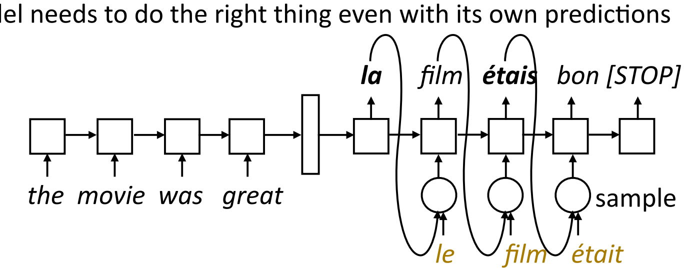
Training



- 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

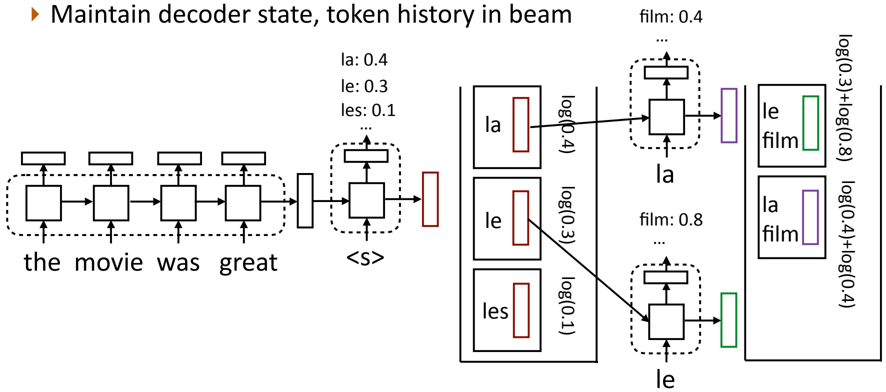
Implementation Details (cont'd)

- 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

Takeaways

- Can represent meaning with first order logic and lambda calculus
- Can bridge syntax and semantics and create semantic parsers that can interpret language into lambda-calculus expressions
- seq2seq models provide an easier way to do this
- Next time: continue seq2seq semantic parsing, discuss *attention*