Natural Language Processing

Berkeley
N L P

Compositional Semantics

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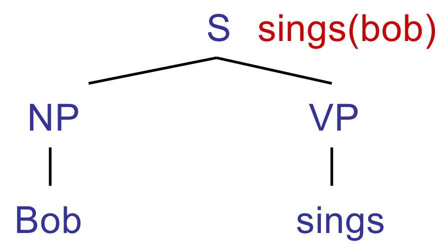
Truth-Conditional Semantics

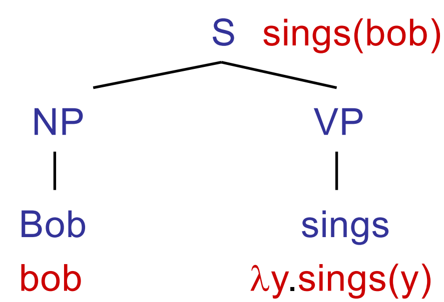
Truth-Conditional Semantics

- Linguistic expressions:
  - “Bob sings”
- Logical translations:
  - sings(bob)
  - Could be p_1218(e_397)
- Denotation:
  - [[bob]] = some specific person (in some context)
  - [[sings(bob)]] = ???
- Types on translations:
  - bob : e (for entity)
  - sings(bob) : t (for truth-value)



Truth-Conditional Semantics

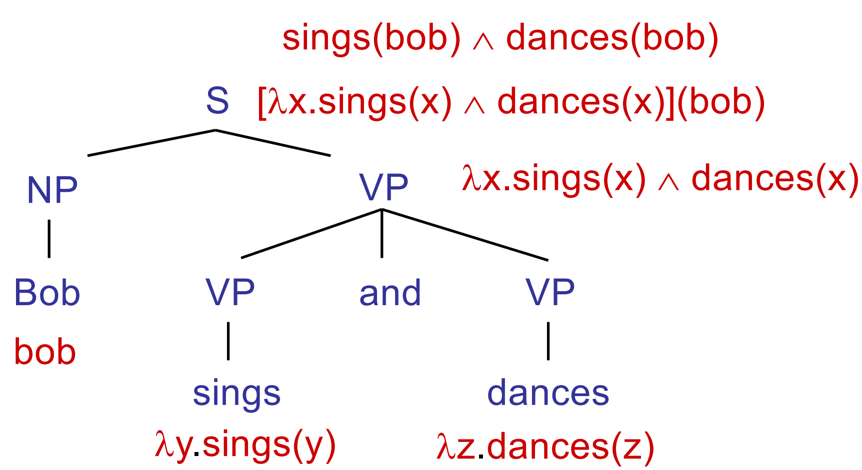
- Proper names:
  - Refer directly to some entity in the world
  - Bob : bob $[[\text{bob}]]^W \rightarrow$???
- Sentences:
  - Are either true or false (given how the world actually is)
  - Bob sings : sings(bob)



- So what about verbs (and verb phrases)?
  - sings must combine with bob to produce sings(bob)
  - The λ-calculus is a notation for functions whose arguments are not yet filled.
  - sings : λx.sings(x)
  - This is a *predicate* – a function which takes an entity (type e) and produces a truth value (type t). We can write its type as $e \rightarrow t$.
  - Adjectives?

Compositional Semantics

- So now we have meanings for the words
- How do we know how to combine words?
- Associate a combination rule with each grammar rule:
  - $S : \beta(\alpha) \rightarrow NP : \alpha \quad VP : \beta$ (function application)
  - $VP : \lambda x . \alpha(x) \wedge \beta(x) \rightarrow VP : \alpha \quad \text{and} : \varnothing \quad VP : \beta$ (intersection)
- Example:

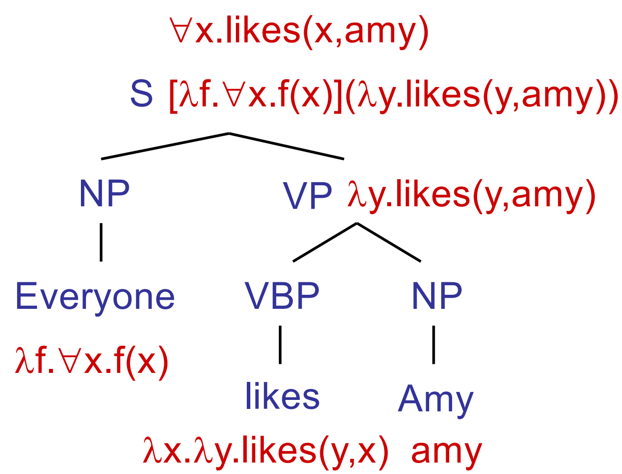


Denotation

- What do we do with logical translations?
  - Translation language (logical form) has fewer ambiguities
  - Can check truth value against a database
    - Denotation ("evaluation") calculated using the database
  - Or the opposite: assert truth and modify a database, either explicitly or implicitly eg prove a consequence from asserted axioms
  - Questions: check whether a statement in a corpus entails the (question, answer) pair:
    - "Bob sings and dances" $\rightarrow$ "Who sings?" + "Bob"
  - Chain together facts and use them for comprehension

Other Cases

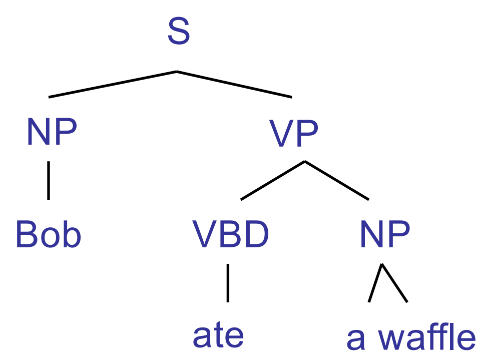
- Transitive verbs:
  - likes : λx.λy.likes(y,x)
  - Two-place predicates of type $e \to (e \to t)$.
  - likes Amy : λy.likes(y,Amy) is just like a one-place predicate.
- Quantifiers:
  - What does "Everyone" mean here?
  - Everyone : λf.∀x.f(x)
  - Mostly works, but some problems
    - Have to change our NP/VP rule.
    - Won't work for "Amy likes everyone."
  - "Everyone likes someone."
  - This gets tricky quickly!



Indefinites

- First try
  - “Bob ate a waffle” : ate(bob,waffle)
  - “Amy ate a waffle” : ate(amy,waffle)

- Can’t be right!
  - $\exists$ x : waffle(x) $\wedge$ ate(bob,x)
  - What does the translation of “a” have to be?
  - What about “the”?
  - What about “every”?



Grounding

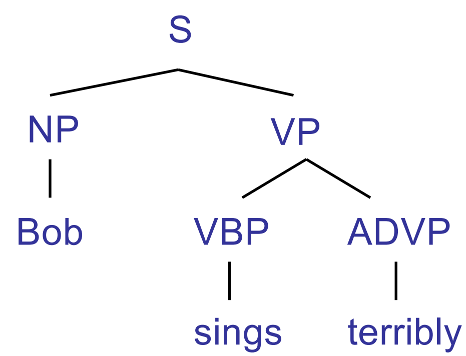
- Grounding
  - So why does the translation likes : $\lambda x.\lambda y.likes(y,x)$ have anything to do with actual liking?
  - It doesn't (unless the denotation model says so)
  - Sometimes that's enough: wire up bought to the appropriate entry in a database
- Meaning postulates
  - Insist, e.g $\forall x,y.likes(y,x) \rightarrow knows(y,x)$
  - This gets into lexical semantics issues
- Statistical / neural version?

Tense and Events

- In general, you don't get far with verbs as predicates
- Better to have event variables e
  - "Alice danced" : danced(alice)
  - $\exists$ e : dance(e) $\wedge$ agent(e,alice) $\wedge$ (time(e) < now)
- Event variables let you talk about non-trivial tense / aspect structures
  - "Alice had been dancing when Bob sneezed"
  - $\exists$ e, e' : dance(e) $\wedge$ agent(e,alice) $\wedge$
    sneeze(e') $\wedge$ agent(e',bob) $\wedge$
    (start(e) < start(e') $\wedge$ end(e) = end(e')) $\wedge$
    (time(e') < now)
- Minimal recursion semantics, cf "object oriented" thinking

Adverbs

- What about adverbs?
  - "Bob sings terribly"
  - terribly(sings(bob))?
  - (terribly(sings))(bob)?
  - ∃e present(e) ∧ type(e, singing) ∧ agent(e,bob) ∧ manner(e, terrible) ?
  - Gets complex quickly…



Propositional Attitudes

- "Bob thinks that I am a gummi bear"
  - thinks(bob, gummi(me)) ?
  - thinks(bob, "I am a gummi bear") ?
  - thinks(bob, ^gummi(me)) ?
- Usual solution involves intensions (^X) which are, roughly, the set of possible worlds (or conditions) in which X is true
- Hard to deal with computationally
  - Modeling other agents' models, etc
  - Can come up in even simple dialog scenarios, e.g., if you want to talk about what your bill claims you bought vs. what you actually bought

Trickier Stuff

- Non-Intersective Adjectives
  - green ball : $\lambda x.[green(x) \wedge ball(x)]$
  - fake diamond : $\lambda x.[fake(x) \wedge diamond(x)]$? $\longrightarrow$ $\lambda x.[fake(diamond(x))$
- Generalized Quantifiers
  - the : $\lambda f.[\textit{unique-member}(f)]$
  - all : $\lambda f.\ \lambda g\ [\forall x.f(x) \rightarrow g(x)]$
  - most?
  - Could do with more general second order predicates, too (why worse?)
    - the(cat, meows), all(cat, meows)
- Generics
  - "Cats like naps"
  - "The players scored a goal"
- Pronouns (and bound anaphora)
  - "If you have a dime, put it in the meter."

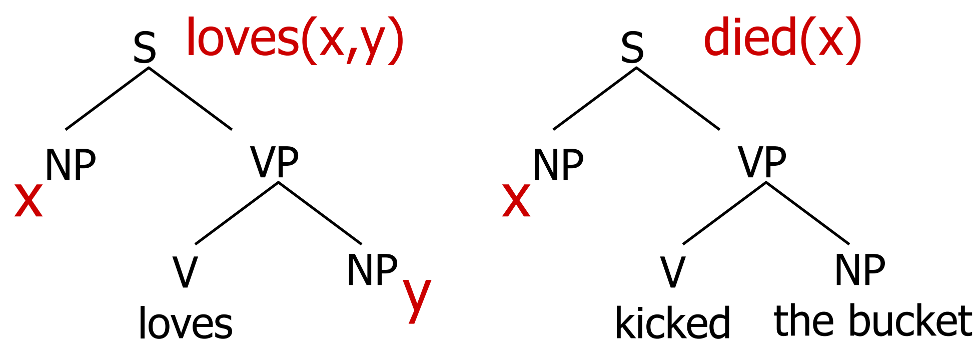
- … the list goes on and on!

Scope Ambiguities

- Quantifier scope
  - "All majors take a data science class"
  - "Someone took each of the electives"
  - "Everyone didn't hand in their exam"
- Deciding between readings
  - Multiple ways to work this out
    - Make it syntactic (movement)
    - Make it lexical (type-shifting)

Classic Implementation, TAG, Idioms

- Add a "sem" feature to each context-free rule
  - S $\longrightarrow$ NP loves NP
  - S[sem=loves(x,y)] $\longrightarrow$ NP[sem=x] loves NP[sem=y]
  - Meaning of S depends on meaning of NPs
- TAG version:



- Template filling: S[sem=showflights(x,y)] $\rightarrow$
  I want a flight from NP[sem=x] to NP[sem=y]

Logical Form Translation

Mapping to LF: Zettlemoyer & Collins 05/07

The task:

Input: `List one way flights to Prague.`

Output: $\lambda x.flight(x) \wedge one\_way(x) \wedge to(x, PRG)$

Challenging learning problem:

- Derivations (or parses) are not annotated
- Approach: [Zettlemoyer & Collins 2005]
- Learn a lexicon and parameters for a weighted Combinatory Categorial Grammar (CCG)

[Slides from Luke Zettlemoyer]

Background

- Combinatory Categorial Grammar (CCG)
- Weighted CCGs
- Learning lexical entries: GENLEX

CCG Parsing

- Combinatory Categorial Grammar
  - Fully (mono-) lexicalized grammar
  - Categories encode argument sequences
  - Very closely related to the lambda calculus
  - Can have spurious ambiguities (why?)

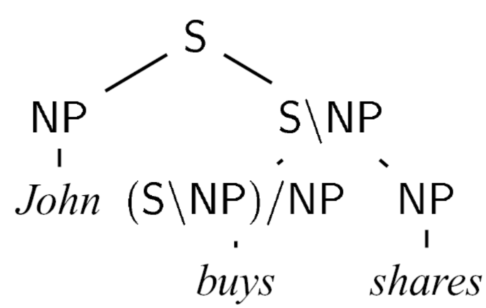
$$John \vdash \mathsf{NP} : john'$$

$$shares \vdash \mathsf{NP} : shares'$$

$$buys \vdash (\mathsf{S}\backslash\mathsf{NP})/\mathsf{NP} : \lambda x.\lambda y.buys'xy$$

$$sleeps \vdash \mathsf{S}\backslash\mathsf{NP} : \lambda x.sleeps'x$$

$$well \vdash (\mathsf{S}\backslash\mathsf{NP})\backslash(\mathsf{S}\backslash\mathsf{NP}) : \lambda f.\lambda x.well'(fx)$$



CCG Lexicon

Words	Category
flights	N : $\lambda x.flight(x)$
to	(N\N)/NP : $\lambda x.\lambda f.\lambda y.f(x) \wedge to(y,x)$
Prague	NP : PRG
New York city	NP : NYC
...	...

Parsing Rules (Combinators)

Application

- `X/Y : f      Y : a   =>   X : f(a)`
- `  Y : a    X\Y : f   =>   X : f(a)`

Composition

- `X/Y : f   Y/Z : g   =>  X/Z : λx.f(g(x))`
- `Y\Z : f   X\Y : g   =>  X\Z : λx.f(g(x))`

Additional rules:

- Type Raising
- Crossed Composition

CCG Parsing

Show me | flights | to | Prague

S/N | N | (N\N)/NP | NP

$\lambda f.f$ | $\lambda x.flight(x)$ | $\lambda y.\lambda f.\lambda x.f(y) \land to(x,y)$ | PRG

N\N

$\lambda f.\lambda x.f(x) \land to(x,PRG)$

N

$\lambda x.flight(x) \land to(x,PRG)$

S

$\lambda x.flight(x) \land to(x,PRG)$

Weighted CCG

Given a log-linear model with a CCG lexicon Λ, a feature vector f, and weights w.

- The best parse is:

$$y^* = \underset{y}{\operatorname{argmax}}\ w \cdot f(x,y)$$

Where we consider all possible parses y for the sentence x given the lexicon Λ.

Lexical Generation

Input Training Example

Sentence:	`Show me flights to Prague.`
Logic Form:	$\lambda x.flight(x) \wedge to(x, PRG)$

Output Lexicon

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

GENLEX: Substrings X Categories

Input Training Example

Sentence:	`Show me flights to Prague.`
Logic Form:	$\lambda x.flight(x) \wedge to(x,PRG)$

Output Lexicon

All possible substrings:

```
Show
me
flights
...
Show me
Show me flights
Show me flights to
...
```

X

Categories created by rules that trigger on the logical form:

$NP : PRG$

$N : \lambda x.flight(x)$

$(S\backslash NP)/NP : \lambda x.\lambda y.to(y,x)$

$(N\backslash N)/NP : \lambda y.\lambda f.\lambda x. \ldots$

...

[Zettlemoyer & Collins 2005]

Robustness

The lexical entries that work for:

```
Show me   the latest   flight   from Boston   to Prague   on Friday
 S/NP       NP/N         N         N\N          N\N          N\N
  ...        ...        ...        ...          ...          ...
```

Will not parse:

```
Boston   to Prague   the latest   on Friday
  NP        N\N         NP/N         N\N
  ...       ...         ...          ...
```

Relaxed Parsing Rules

Two changes

- Add application and composition rules that relax word order
- Add type shifting rules to recover missing words

These rules significantly relax the grammar

- Introduce features to count the number of times each new rule is used in a parse

Review: Application

```
X/Y : f      Y : a    =>   X : f(a)
Y : a      X\Y : f    =>   X : f(a)
```

Disharmonic Application

- Reverse the direction of the principal category:

```
X\Y : f      Y : a    =>   X : f(a)
Y : a      X/Y : f    =>   X : f(a)
```

$$
\dfrac{\dfrac{\textbf{flights}}{\begin{array}{c}\mathbf{N}\\ \lambda x.flight(x)\end{array}} \qquad \dfrac{\textbf{one way}}{\begin{array}{c}\mathbf{N/N}\\ \lambda f.\lambda x.f(x)\wedge one\_way(x)\end{array}}}{\begin{array}{c}\mathbf{N}\\ \lambda x.flight(x)\wedge one\_way(x)\end{array}}
$$

Missing content words

Insert missing semantic content

- NP : c => N\N : $\lambda f.\lambda x.f(x) \wedge p(x,c)$

$$
\dfrac{\dfrac{\textbf{flights}}{\begin{array}{c}\textbf{N}\\ \lambda x.flight(x)\end{array}} \quad \dfrac{\dfrac{\textbf{Boston}}{\begin{array}{c}\textbf{NP}\\ BOS\end{array}}}{\begin{array}{c}\textbf{N}\backslash\textbf{N}\\ \lambda f.\lambda x.f(x)\wedge from(x,\mathrm{BOS})\end{array}}}{\begin{array}{c}\textbf{N}\\ \lambda x.flight(x)\wedge from(x,\mathrm{BOS})\end{array}} \quad \dfrac{\textbf{to Prague}}{\begin{array}{c}\textbf{N}\backslash\textbf{N}\\ \lambda f.\lambda x.f(x)\wedge to(x,\mathrm{PRG})\end{array}}
$$

$$
\begin{array}{c}\textbf{N}\\ \lambda x.flight(x)\wedge from(x,\mathrm{BOS})\wedge to(x,\mathrm{PRG})\end{array}
$$

Missing content-free words

Bypass missing nouns

- N\N : f => N : f(λx.true)

$$
\begin{array}{cc}
\textbf{Northwest Air} & \textbf{to Prague} \\
\hline
\mathbf{N/N} & \mathbf{N\backslash N} \\
\lambda f.\lambda x.f(x)\wedge airline(x,\mathrm{NWA}) & \lambda f.\lambda x.f(x)\wedge to(x,\mathrm{PRG}) \\
\cline{2-2}
 & \mathbf{N} \\
 & \lambda x.to(x,\mathrm{PRG}) \\
\hline
\multicolumn{2}{c}{\mathbf{N}} \\
\multicolumn{2}{c}{\lambda x.airline(x,\mathrm{NWA})\ \wedge\ to(x,\mathrm{PRG})}
\end{array}
$$

Inputs: Training set $\{(x_i, z_i) \mid i=1 \ldots n\}$ of sentences and logical forms. Initial lexicon Λ. Initial parameters w. Number of iterations T.

Training: For $t = 1 \ldots T$, $i = 1 \ldots n$:

Step 1: Check Correctness

- Let $y^* = \operatorname*{argmax}_y w \cdot f(x_i, y)$
- If $L(y^*) = z_i$, go to the next example

Step 2: Lexical Generation

- Set $\lambda = \Lambda \bigcup \text{GENLEX}(x_i, z_i)$
- Let $\hat{y} = \arg \max_{y \text{ s.t. } L(y)=z_i} w \cdot f(x_i, y)$
- Define λ_i to be the lexical entries in y^
- Set lexicon to $\Lambda = \Lambda \cup \lambda_i$

Step 3: Update Parameters

- Let $y' = \operatorname*{argmax}_y w \cdot f(x_i, y)$
- If $L(y') \neq z_i$
    - Set $w = w + f(x_i, \hat{y}) - f(x_i, y')$

Output: Lexicon Λ and parameters w.

Neural Encoder-Decoder Approaches

Encoder-Decoder Models

- 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

Next slides from Greg Durrett

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

Semantic Parsing as Seq2Seq

"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)

Problem: Lack of Inductive Bias

"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

Possible Solution: 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

Possible Solution: Copying

	GEO	ATIS
No Copying	74.6	69.9
With Copying	85.0	76.3

- For semantic parsing, copying tokens from the input (*texas*) can be very useful
- Copying typically helps a bit, but attention captures most of the benefit. However, vocabulary expansion is critical for some tasks (machine translation)

Jia and Liang (2016)

Mapping to Programs

```
show me the fare from ci0 to ci1

lambda $0 e
  ( exists $1 ( and ( from $1 ci0 )
                    ( to $1 ci1 )
                    ( = ( fare $1 ) $0 ) ) )
```


```
name: [
  'D', 'i', 'r', 'e', ' ',
  'W', 'o', 'l', 'f', ' ',
  'A', 'l', 'p', 'h', 'a']
cost: ['2']
type: ['Minion']
rarity: ['Common']
race: ['Beast']
class: ['Neutral']
description: [
  'Adjacent', 'minions', 'have',
  '+', '1', 'Attack', '.']
health: ['2']
attack: ['2']
durability: ['-1']
```

```
class DireWolfAlpha(MinionCard):
  def __init__(self):
    super().__init__(
      "Dire Wolf Alpha", 2, CHARACTER_CLASS.ALL,
      CARD_RARITY.COMMON, minion_type=MINION_TYPE.BEAST)
  def create_minion(self, player):
    return Minion(2, 2, auras=[
      Aura(ChangeAttack(1), MinionSelector(Adjacent()))
    ])
```

[Rabinovich, Stern, Klein, 2017]

Structured Models

- Meaning representations (e.g., Python) have strong underlying syntax
- How can we **explicitly** model the underlying syntax/grammar of the target meaning representations in the decoding process?

Python Abstract Grammar

expr ⟼ Name | Call

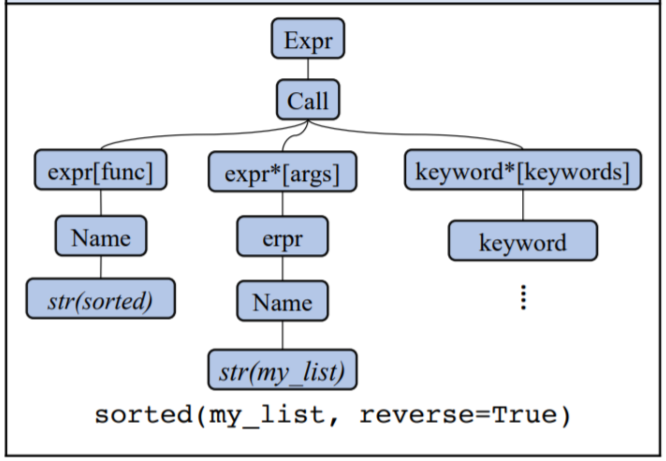
Call ⟼ expr[*func*] expr*[*args*] keyword*[*keywords*]

If ⟼ expr[*test*] stmt*[*body*] stmt*[*orelse*]

For ⟼ expr[*target*] expr*[*iter*] stmt*[*body*] stmt*[*orelse*]

FunctionDef ⟼ identifier[*name*] expr*[*iter*] stmt*[*body*] stmt*[*orelse*]

Abstract Syntax Tree



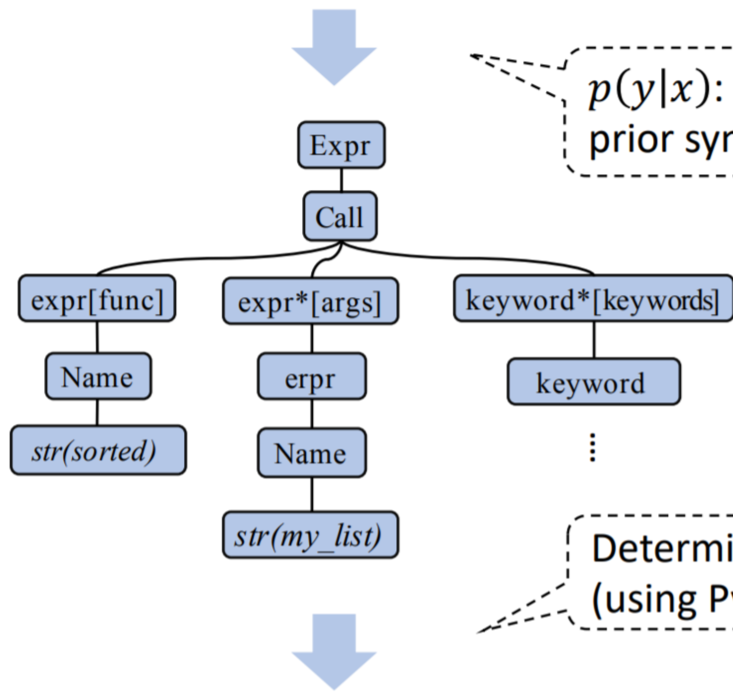
Next section includes slides from Yin / Neubig

Abstract Syntax Trees

Input Intent (x) *sort my_list in descending order*

$p(y|x)$: a seq2seq model with prior syntactic information

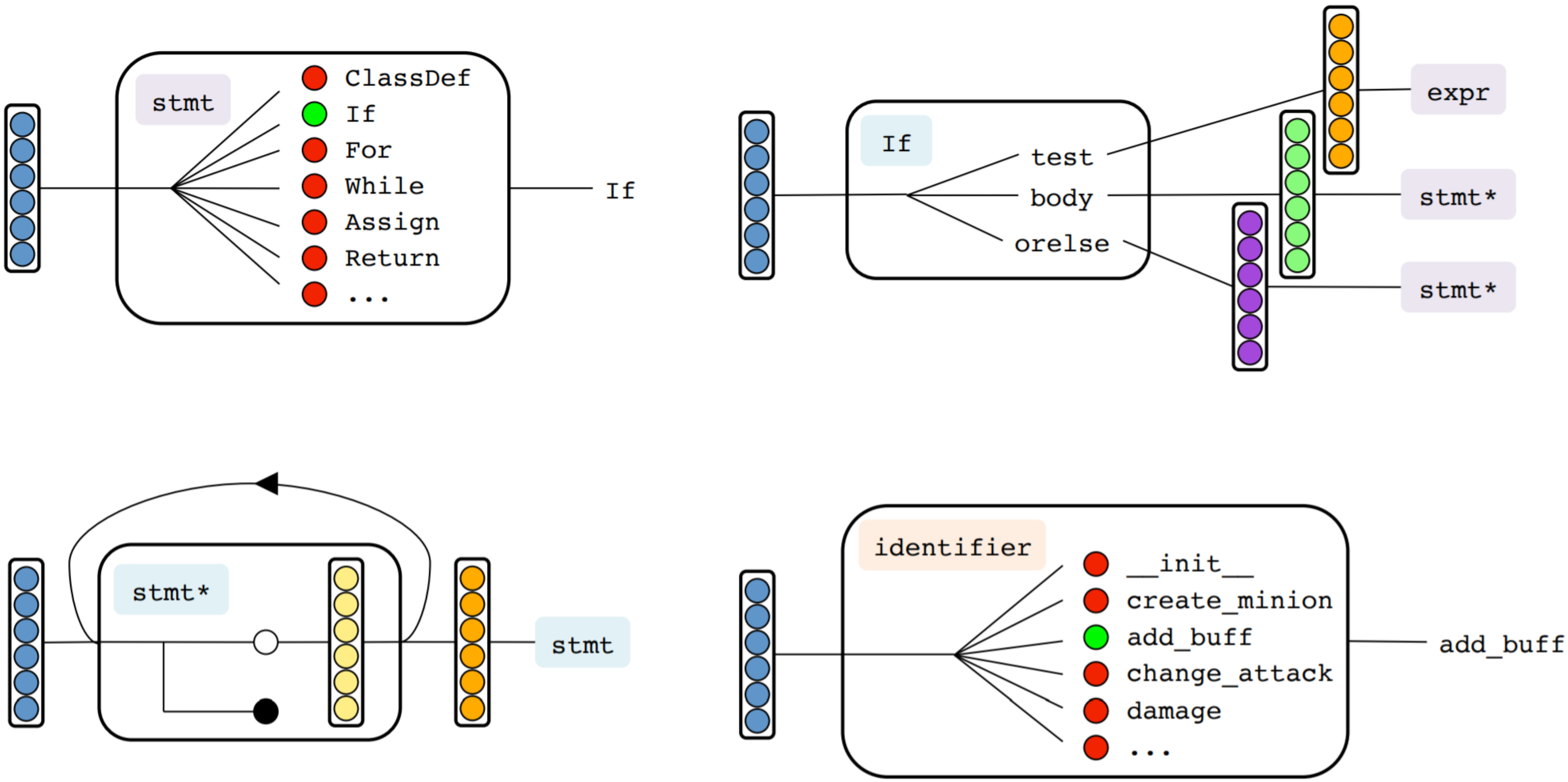
Generated AST (y)



Deterministic transformation (using Python `astor` library)

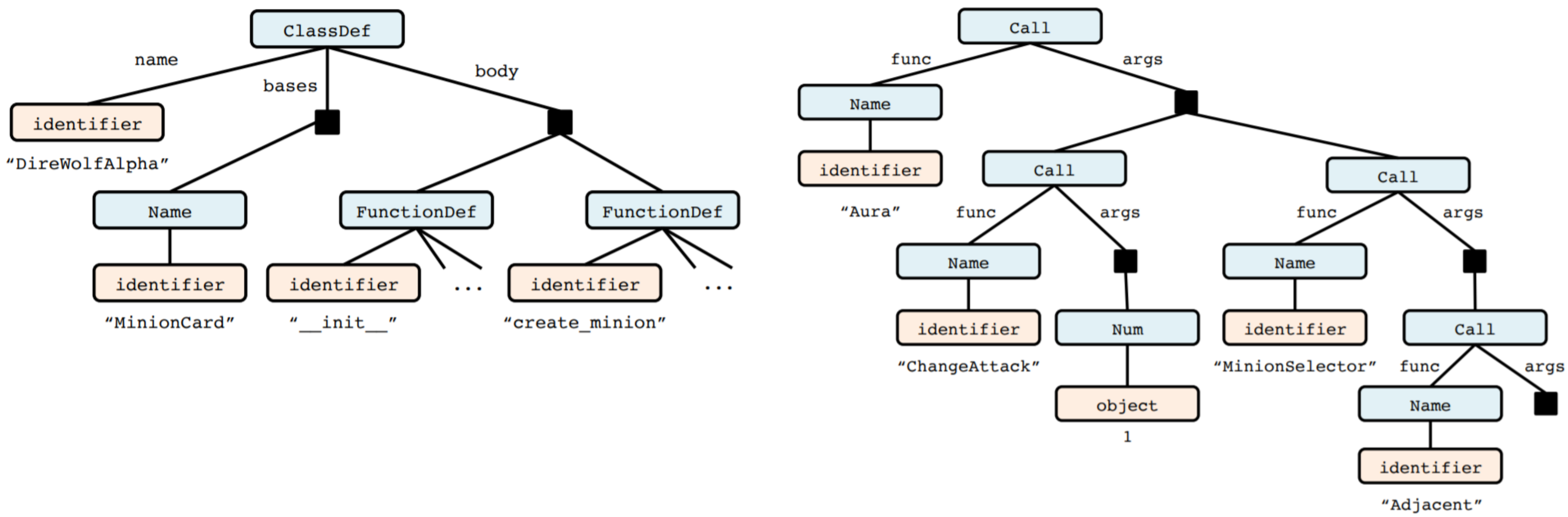
Surface Code (c) `sorted(my_list, reverse=True)`

AST-Structured Neural Modules



[Rabinovich, Stern, Klein, 2017]

AST-Structured Fragments



Example Results Across Tasks

ATIS System	ATIS Accuracy	GEO System	GEO Accuracy	JOBS System	JOBS Accuracy
ZH15	84.2	ZH15	88.9	ZH15	85.0
ZC07	84.6	KCAZ13	89.0	PEK03	88.0
WKZ14	**91.3**	WKZ14	**90.4**	LJK13	90.7
DL16	84.6	DL16	87.1	DL16	90.0
ASN	85.3	ASN	85.7	ASN	**91.4**
+ SUPATT	85.9	+ SUPATT	87.1	+ SUPATT	**92.9**

[Rabinovich, Stern, Klein, 2017]

Copying / Pointer Networks

Intent *join app_config.path and string 'locale' into a file path, substitute it for localedir.*

Pred.
```
localedir = os.path.join(app_config.path, 'locale') ✓
```

Intent *self.plural is an lambda function with an argument n, which returns result of boolean expression n not equal to integer 1*

Pred.
```
self.plural = lambda n: len(n) ✗
```

Ref.
```
self.plural = lambda n: int(n!=1)
```

Intent *<name> Burly Rockjaw Trogg </name> <cost> 5 </cost> <attack> 3 </attack> <defense> 5 </defense> <desc> Whenever your opponent casts a spell, gain 2 Attack. </desc> <rarity> Common </rarity> ...*

Ref.
```
class BurlyRockjawTrogg(MinionCard):
    def __init__(self):
        super().__init__('Burly Rockjaw Trogg', 4, CHARACTER_CLASS.ALL, CARD_RARITY.COMMON)
    def create_minion(self, player):
        return Minion(3, 5, effects=[Effect(SpellCast(player=EnemyPlayer()),
            ActionTag(Give(ChangeAttack(2)), SelfSelector()))]) ✓
```