The Challenge of Composition in Distributional and Formal Semantics Part II

Ran Tian[1], Koji Mineshima[2] and Pascual Martínez-Gómez[3]

[1]Tohoku University, Japan
[2]Ochanomizu University, Japan
[3]AIST, Japan

November 27, 2017

Three Challenges

1. Meaning Representations (MRs): what are proper MRs for natural languages?
2. Compositional Semantics: how to compute the MR of a complex expression from the MRs of its parts?
3. Inference: how can we do inference with MRs?

- We start with Question 2:
  - Combinatory Categorial Grammar (CCG)
  - Lambda Calculus
- And then move on to Question 1 and Question 3
  - First-order and Higher-order Logics
  - A MR is good if it enables correct and efficient inferences

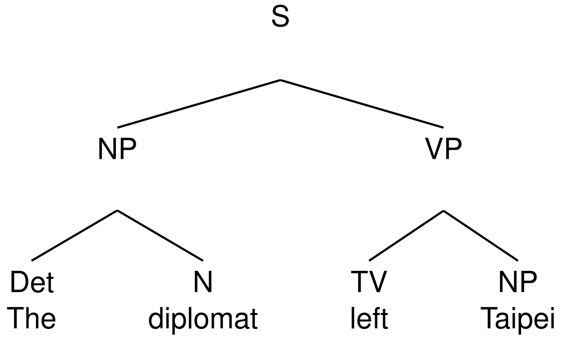
Semantic Composition via Phrase Structure Grammar

S $\rightarrow$ NP VP

NP $\rightarrow$ Det N

VP $\rightarrow$ TV NP

Det $\rightarrow$ the
N $\rightarrow$ diplomat
NP $\rightarrow$ Taipei
TV $\rightarrow$ left



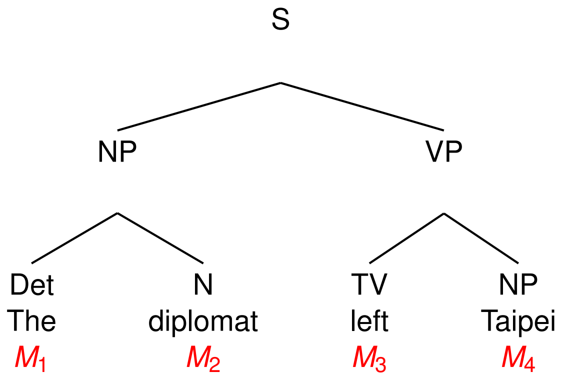
Semantic Composition via Phrase Structure Grammar

S → NP VP

NP → Det N

VP → TV NP

Det → the
N → diplomat
NP → Taipei
TV → left



- Assign a MR to each leaf node

Semantic Composition via Phrase Structure Grammar

S $\rightarrow$ NP VP

NP $\rightarrow$ Det N

$[\![NP]\!] = [\![Det]\!] \oplus_2 [\![N]\!]$

VP $\rightarrow$ TV NP

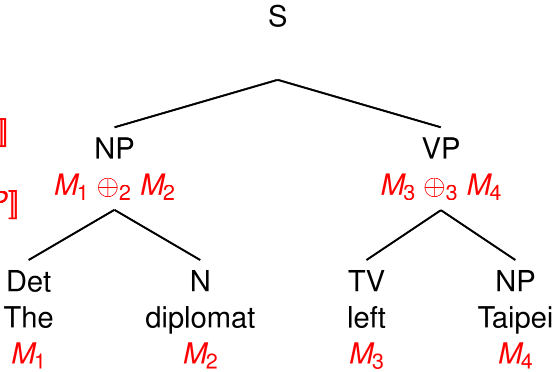
$[\![VP]\!] = [\![TV]\!] \oplus_3 [\![NP]\!]$

Det $\rightarrow$ the

N $\rightarrow$ diplomat

NP $\rightarrow$ Taipei

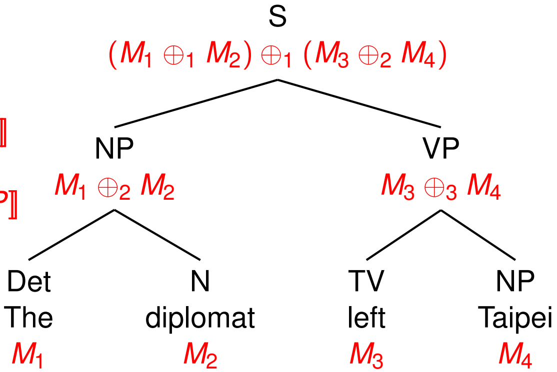
TV $\rightarrow$ left



- Assign a MR to each leaf node
- Compute the MR of each phrase in terms of the MRs of its parts, according to meaning composition rules

Semantic Composition via Phrase Structure Grammar

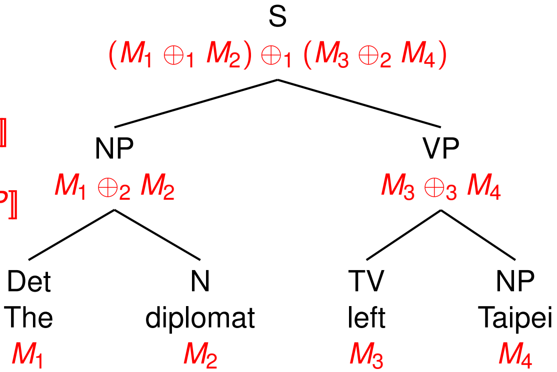
$$
\begin{array}{rcl}
\text{S} & \rightarrow & \text{NP VP} \\
\multicolumn{3}{l}{[\![S]\!] = [\![NP]\!] \oplus_1 [\![VP]\!]} \\
\text{NP} & \rightarrow & \text{Det N} \\
\multicolumn{3}{l}{[\![NP]\!] = [\![Det]\!] \oplus_2 [\![N]\!]} \\
\text{VP} & \rightarrow & \text{TV NP} \\
\multicolumn{3}{l}{[\![VP]\!] = [\![TV]\!] \oplus_3 [\![NP]\!]} \\
\text{Det} & \rightarrow & \text{the} \\
\text{N} & \rightarrow & \text{diplomat} \\
\text{NP} & \rightarrow & \text{Taipei} \\
\text{TV} & \rightarrow & \text{left}
\end{array}
$$



- Assign a MR to each leaf node
- Compute the MR of each phrase in terms of the MRs of its parts, according to meaning composition rules

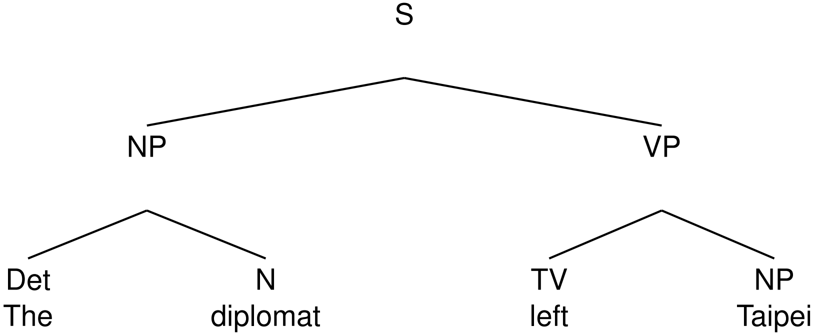
Semantic Composition via Phrase Structure Grammar

$$\begin{array}{rcl} \mathrm{S} & \rightarrow & \mathrm{NP\ VP} \\ & [\![S]\!] = [\![NP]\!] \oplus_1 [\![VP]\!] & \\ \mathrm{NP} & \rightarrow & \mathrm{Det\ N} \\ & [\![NP]\!] = [\![Det]\!] \oplus_2 [\![N]\!] & \\ \mathrm{VP} & \rightarrow & \mathrm{TV\ NP} \\ & [\![VP]\!] = [\![TV]\!] \oplus_3 [\![NP]\!] & \\ \mathrm{Det} & \rightarrow & \mathrm{the} \\ \mathrm{N} & \rightarrow & \mathrm{diplomat} \\ \mathrm{NP} & \rightarrow & \mathrm{Taipei} \\ \mathrm{TV} & \rightarrow & \mathrm{left} \end{array}$$

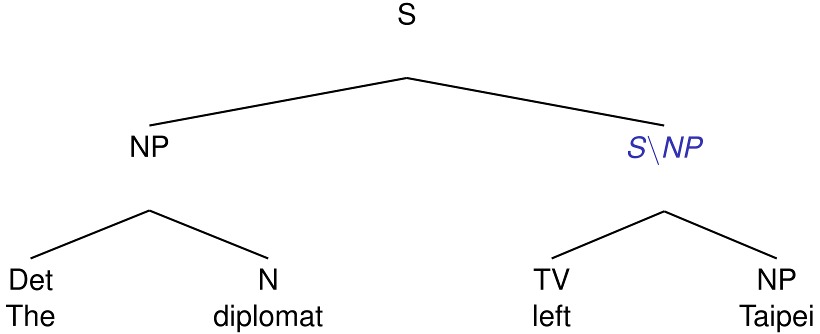


- Assign a MR to each leaf node
- Compute the MR of each phrase in terms of the MRs of its parts, according to meaning composition rules
- Many grammar rules, many composition rules

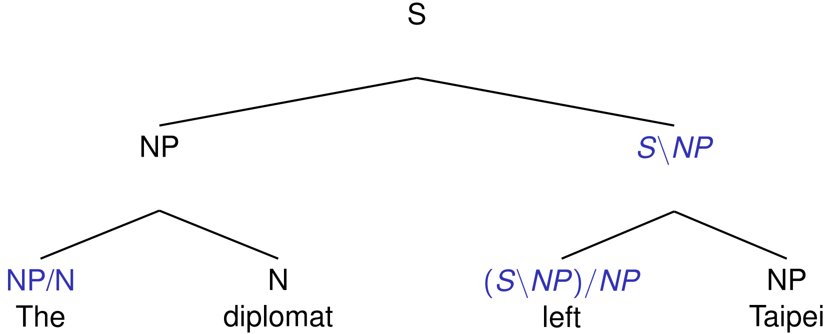
Semantic Composition via Categorial Grammar (CG)



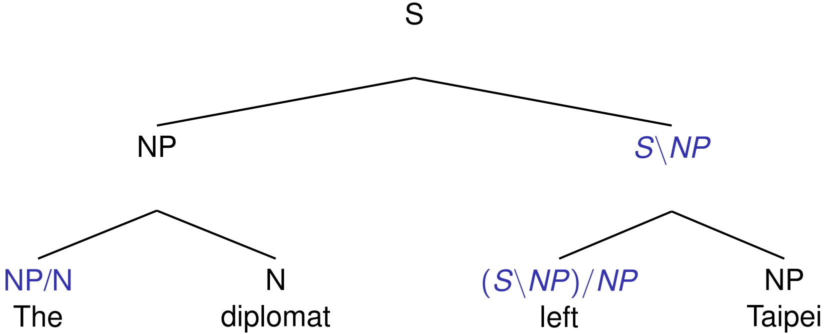
Semantic Composition via Categorial Grammar (CG)



Semantic Composition via Categorial Grammar (CG)

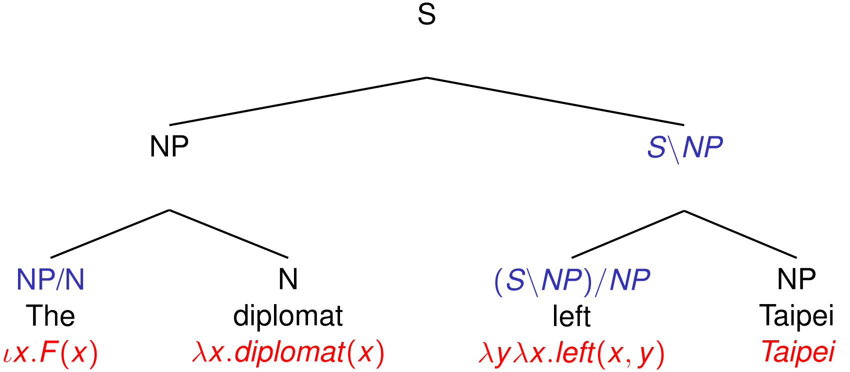


Semantic Composition via Categorial Grammar (CG)



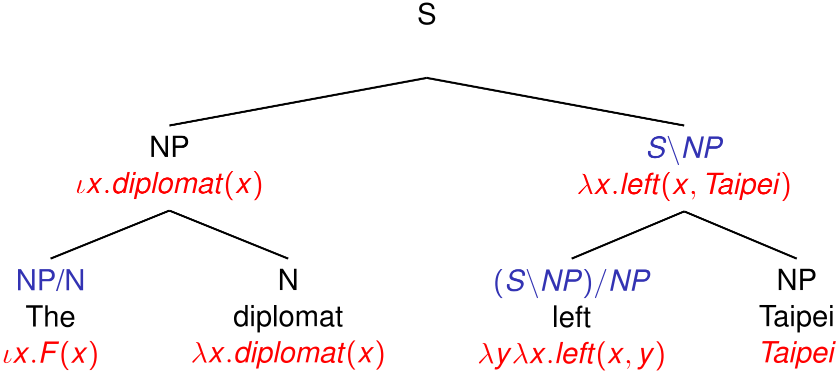
- A small set of basic categories (S, NP, N)
- Each functional category of the form X/Y and $X\backslash Y$ specifies how words combine with each other

Semantic Composition via Categorial Grammar (CG)



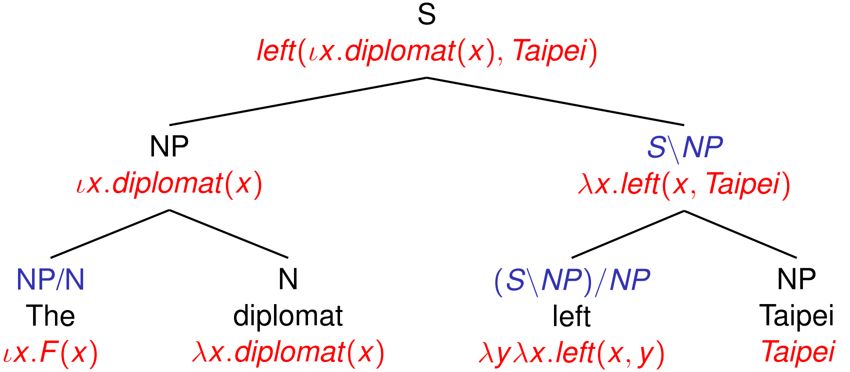
- A small set of basic categories (S, NP, N)
- Each functional category of the form X/Y and $X\backslash Y$ specifies how words combine with each other and, at the same time, how to compute the MR of a phrase node.

Semantic Composition via Categorial Grammar (CG)



- A small set of basic categories (S, NP, N)
- Each functional category of the form X/Y and $X\backslash Y$ specifies how words combine with each other and, at the same time, how to compute the MR of a phrase node.

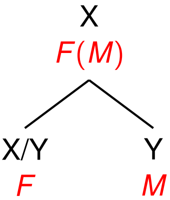
Semantic Composition via Categorial Grammar (CG)



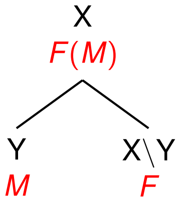
- A small set of basic categories (S, NP, N)
- Each functional category of the form X/Y and $X \backslash Y$ specifies how words combine with each other and, at the same time, how to compute the MR of a phrase node.
- A small set of grammar rules and meaning composition rules

Combinatory Rules

Forward Function Application



Backward Function Application



Derivation trees

- Turn the tree upside down (for a historical reason)
- Derivation trees (proof trees)

$$\dfrac{\dfrac{\texttt{John}}{\begin{array}{c}NP\\ john\end{array}} \qquad \dfrac{\dfrac{\texttt{likes}}{\begin{array}{c}(S\backslash NP)/NP\\ \lambda y.\lambda x.like(x,y)\end{array}} \quad \dfrac{\texttt{Mary}}{\begin{array}{c}NP\\ mary\end{array}}}{\begin{array}{c}S\backslash NP\\ \lambda x.like(x,mary)\end{array}}\ >}{\begin{array}{c}S\\ like(john,mary)\end{array}}\ <$$

- Function Application rules

$$\dfrac{\begin{array}{c}X/Y\\ F\end{array} \qquad \begin{array}{c}Y\\ M\end{array}}{\begin{array}{c}X\\ F(M)\end{array}}\ > \qquad\qquad \dfrac{\begin{array}{c}Y\\ M\end{array} \qquad \begin{array}{c}X\backslash Y\\ F\end{array}}{\begin{array}{c}X\\ F(M)\end{array}}\ <$$

From AB to CCG

- The fragment of categorial grammar consisting of function application rules is called AB grammar (Ajdukiewicz, 1935; Bar-Hillel, 1953)
- Adding more combinatory rules leads to Combinatory Categorial Grammar (CCG) (Steedman, 2000, 2012)

More combinatory rules

Function Composition rules

$$\frac{\underset{f}{X/Y} \qquad \underset{g}{Y/Z}}{\underset{\lambda x.f(g(x))}{X/Z}} > \mathbf{B} \qquad \frac{\underset{g}{Y\backslash Z} \qquad \underset{f}{X\backslash Y}}{\underset{\lambda x.f(g(x))}{X\backslash Z}} < \mathbf{B}$$

Crossed Composition rules

$$\frac{\underset{f}{X/Y} \qquad \underset{g}{Y\backslash Z}}{\underset{\lambda x.f(g(x))}{X\backslash Z}} > \mathbf{B}_\times \qquad \frac{\underset{g}{Y/Z} \qquad \underset{f}{X\backslash Y}}{\underset{\lambda x.f(g(x))}{X/Z}} < \mathbf{B}_\times$$

A more complicated derivation

John doesn't like Mary

$\neg like(john, mary)$

$$
\dfrac{
\dfrac{\texttt{John}}{\begin{array}{c} NP \\ john \end{array}}
\qquad
\dfrac{
\dfrac{
\dfrac{\texttt{doesn't}}{\begin{array}{c} (S\backslash NP)/(S\backslash NP) \\ \lambda Fx.\neg F(x) \end{array}}
\quad
\dfrac{\texttt{like}}{\begin{array}{c} (S\backslash NP)/NP \\ \lambda y.\lambda x.like(x, y) \end{array}}
}{\begin{array}{c} (S\backslash NP)/NP \\ \lambda x.\neg like(x, mary) \end{array}}\; {>}\mathbf{B}
\quad
\dfrac{\texttt{Mary}}{\begin{array}{c} NP \\ mary \end{array}}
}{\begin{array}{c} S\backslash NP \\ \lambda x.\neg like(x, mary) \end{array}}\; {>}
}{\begin{array}{c} S \\ \neg like(john, mary) \end{array}}\; {<}
$$

Lambda calculus

- A formal system to represent computation
- Simple yet very expressive

function	input	output
$\lambda x.x + 2$	number x	$x + 2$
$\lambda x.walk(x)$	entity x	proposition $walk(x)$

β-conversion (simplification, substitution):

$$\overbrace{(\lambda x.[\ldots\ x\ \ldots])}^{\text{function}}\ \overbrace{(a)}^{\text{argument}} = [\ \ldots\ a\ \ldots\ ]$$

Examples:

- $(\lambda x.x + 2)(5) = 5 + 2$
- $(\lambda x.walk(x))(john) = walk(john)$

β-conversion: more examples

β-conversion (simplification):

$$\underbrace{(\lambda x.[\ldots\ x\ \ldots])}_{\text{function}}\ \underbrace{(a)}_{\text{argument}} = [\ \ldots\ a\ \ldots\ ]$$

1. $(\lambda x.like(x,y))(john) = like(john,y)$
2. $(\lambda y.like(x,y))(john) = like(x,john)$
3. $(\lambda x.like(x,x))(john) = like(john,john)$
4. $(\lambda x.like(mary,x) \wedge boy(x))(john) = like(mary,john) \wedge boy(john)$
5. $((\lambda y.\lambda x.like(x,y))(john))(mary) =$
   $(\lambda x.like(x,john))(mary) = like(mary,john)$

α-conversion

α-conversion (renaming):

$$\lambda \boxed{x} .[\ldots \boxed{x} \ldots] = \lambda \boxed{y} .[\ldots \boxed{y} \ldots]$$

Example:

$$\lambda x.\mathit{boy}(x) \wedge \mathit{love}(x)(z) \;=\; \lambda y.\mathit{boy}(y) \wedge \mathit{love}(y)(z)$$

α-conversion

α-conversion (renaming):

$$\lambda x.[\ldots x \ldots] = \lambda y.[\ldots y \ldots]$$

Example:

$$\lambda x.\mathit{boy}(x) \wedge \mathit{love}(x)(z) \;=\; \lambda y.\mathit{boy}(y) \wedge \mathit{love}(y)(z)$$

Lambda calculus vs. Set Theory

Lambda calculus	Set Theory
$\lambda x.Fx$	$\{x \mid Fx\}$
$(\lambda x.Fx)(a)$	$a \in \{x \mid Fx\}$
$(\lambda x.Fx)(a) = Fa$	$a \in \{x \mid Fx\} \Leftrightarrow Fa$

Adding type information

- But is meaning composition via lambda calculus always safe?
- What we need: Type safety
- Type safety lies at the heart of formal compositional semantics

Adding type information

- But is meaning composition via lambda calculus always safe?
- What we need: Type safety
- Type safety lies at the heart of formal compositional semantics

Define simple types:

Type	Meaning
$\mathtt{E}$	Entity
$\mathtt{T}$	Proposition
$X \to Y$	A function from X to Y

Examples:

$\mathit{john}, \mathit{mary}$:	$\mathtt{E}$	entity
$\lambda x.\mathit{walk}(x)$:	$\mathtt{E} \to \mathtt{T}$	function from entities to propositions
$\lambda y.\lambda x.\mathit{like}(x, y)$:	$\mathtt{E} \to (\mathtt{E} \to \mathtt{T})$	function from two entities to propositions

Adding type information

- But is meaning composition via lambda calculus always safe?
- What we need: Type safety
- Type safety lies at the heart of formal compositional semantics

Define simple types:

Type	Meaning
$\mathtt{E}$	Entity
$\mathtt{T}$	Proposition
$X \to Y$	A function from X to Y

Examples:

$\mathit{john}, \mathit{mary}$:	$\mathtt{E}$	entity
$\lambda x.\mathit{walk}(x)$:	$\mathtt{E} \to \mathtt{T}$	function from entities to propositions
$\lambda y.\lambda x.\mathit{like}(x, y)$:	$\mathtt{E} \to (\mathtt{E} \to \mathtt{T})$	function from two entities to propositions
$\mathit{walk}(\mathit{john})$:	$\mathtt{T}$	proposition

Adding type information

- But is meaning composition via lambda calculus always safe?
- What we need: Type safety
- Type safety lies at the heart of formal compositional semantics

Define simple types:

Type	Meaning
$\mathtt{E}$	Entity
$\mathtt{T}$	Proposition
$X \to Y$	A function from X to Y

Examples:

$\mathit{john}, \mathit{mary}$:	$\mathtt{E}$	entity
$\lambda x.\mathit{walk}(x)$:	$\mathtt{E} \to \mathtt{T}$	function from entities to propositions
$\lambda y.\lambda x.\mathit{like}(x, y)$:	$\mathtt{E} \to (\mathtt{E} \to \mathtt{T})$	function from two entities to propositions
$\mathit{walk}(\mathit{john})$:	$\mathtt{T}$	proposition
$\mathit{like}(\mathit{john}, \mathit{mary})$:	$\mathtt{T}$	proposition

Adding type information

- But is meaning composition via lambda calculus always safe?
- What we need: Type safety
- Type safety lies at the heart of formal compositional semantics

Define simple types:

Type	Meaning
$\mathtt{E}$	Entity
$\mathtt{T}$	Proposition
$X \rightarrow Y$	A function from X to Y

Examples:

john, *mary* :	$\mathtt{E}$	entity
$\lambda x.walk(x)$:	$\mathtt{E} \rightarrow \mathtt{T}$	function from entities to propositions
$\lambda y.\lambda x.like(x, y)$:	$\mathtt{E} \rightarrow (\mathtt{E} \rightarrow \mathtt{T})$	function from two entities to propositions
$walk(john)$:	$\mathtt{T}$	proposition
$like(john, mary)$:	$\mathtt{T}$	proposition
$walk(like)$:	# type-mismatch	

Types control semantic composition

β-conversion (simplification):

$$\underbrace{(\lambda x.[\ldots\ x\ \ldots])}_{\text{Type: } A \rightarrow B}\ \underbrace{(a)}_{\text{Type: } A} = \underbrace{[\ \ldots\ \text{a}\ \ldots\ ]}_{\text{Type: B}}$$

Example:

$$\underbrace{(\lambda x.walk(x))}_{\text{Type: } \mathtt{E} \rightarrow \mathtt{T}}\quad \underbrace{(john)}_{\text{Type: } \mathtt{E}}\quad = \quad \underbrace{\text{walk(john)}}_{\text{Type: } \mathtt{T}}$$

CCG-based Compositional Semantics

- Type information is always implicit in CCG-derivation trees

$$\dfrac{\mathtt{John}}{\begin{array}{c} NP \\ john \end{array}} \qquad \dfrac{\dfrac{\mathtt{likes}}{\begin{array}{c} (S\backslash NP)/NP \\ \lambda y.\lambda x.like(x, y) \end{array}} \quad \dfrac{\mathtt{Mary}}{\begin{array}{c} NP \\ mary \end{array}}}{\begin{array}{c} S\backslash NP \\ \lambda x.like(x, mary) \end{array}} >$$

$$\dfrac{\begin{array}{c} NP \\ john \end{array} \qquad \begin{array}{c} S\backslash NP \\ \lambda x.like(x, mary) \end{array}}{\begin{array}{c} S \\ like(john, mary) \end{array}} <$$

CCG-based Compositional Semantics

- Type information is always implicit in CCG-derivation trees

$\texttt{likes}$

$(S\backslash NP)/NP$

$\lambda y.\lambda x.like(x,y) : \mathtt{E} \rightarrow (\mathtt{E} \rightarrow \mathtt{T})$

$\texttt{Mary}$

NP

$mary : \mathtt{E}$

$\texttt{John}$

NP

$john : \mathtt{E}$

$>$

$S\backslash NP$

$\lambda x.like(x, mary) : \mathtt{E} \rightarrow \mathtt{T}$

$<$

S

$like(john, mary) : \mathtt{T}$

Syntactic sugar

Special symbols (constants) to represent logical expression:

Logical expression	Type	
$\neg$	$\mathtt{T} \to \mathtt{T}$	negation
$\wedge$	$\mathtt{T} \to \mathtt{T} \to \mathtt{T}$	conjunction
$\vee$	$\mathtt{T} \to \mathtt{T} \to \mathtt{T}$	disjunction
$\to$	$\mathtt{T} \to \mathtt{T} \to \mathtt{T}$	implication
$\forall$	$(\mathtt{E} \to \mathtt{T}) \to \mathtt{T}$	universal quantifier
$\exists$	$(\mathtt{E} \to \mathtt{T}) \to \mathtt{T}$	existential quantifier
ι	$(\mathtt{E} \to \mathtt{T}) \to \mathtt{E}$	iota operator

We can write :

$$\begin{array}{lll} A \wedge B & \text{for} & \wedge(A, B) \\ \forall x F x & \text{for} & \forall(\lambda x. F x) \\ \exists x F x & \text{for} & \exists(\lambda x. F x) \end{array}$$

and so on.

- Logics can be encoded in Lambda calculus!

From categories to types

We can define a homomorphism $(\cdot)^\bullet$ from categories to types:

$$
\begin{aligned}
(NP)^\bullet &= \mathtt{E} \\
(N)^\bullet &= \mathtt{E} \to \mathtt{T} \\
(S)^\bullet &= \mathtt{T} \\
(X/Y)^\bullet = (X\backslash Y)^\bullet &= (X)^\bullet \to (Y)^\bullet
\end{aligned}
$$

Example:

- $(S\backslash NP)^\bullet = \mathtt{E} \to \mathtt{T}$ (intransitive verbs)
- $((S\backslash NP)/NP)^\bullet = \mathtt{E} \to (\mathtt{E} \to \mathtt{T})$ (transitive verbs)
- $((S/(S\backslash NP))/N)^\bullet = (\mathtt{E} \to \mathtt{T}) \to \mathtt{E}$ (determiners)

- As for as the type homomorphism is preserved, there will be no type-clash during meaning composition.

Lexicon: open words and closed words

- For an open word, we can use a template to specify its MR.
- φ is the position in which the lemma appears.

Category	Meaning templates	Type
$S\backslash NP$	$\lambda x.\varphi(x)$	$\mathtt{E} \to \mathtt{T}$
$(S\backslash NP)/NP$	$\lambda y.\lambda x.\varphi(x, y)$	$\mathtt{E} \to (\mathtt{E} \to \mathtt{T})$

- For a closed word, we can directly assign its MR.
- For example, if we are interested in logical expressions, we can use the following lexical entries:

Lemma	Category	MR	Type
some	NP/N	$\lambda F \lambda G.\exists x(Fx \wedge Gx)$	$(\mathtt{E} \to \mathtt{T}) \to (\mathtt{E} \to \mathtt{T}) \to \mathtt{T}$
every	NP/N	$\lambda F \lambda G.\forall x(Fx \wedge Gx)$	$(\mathtt{E} \to \mathtt{T}) \to (\mathtt{E} \to \mathtt{T}) \to \mathtt{T}$
no	NP/N	$\lambda F \lambda G.\neg\exists x(Fx \wedge Gx)$	$(\mathtt{E} \to \mathtt{T}) \to (\mathtt{E} \to \mathtt{T}) \to \mathtt{T}$

Excerpts of Templates from ccg2lambda

CCG category	Meaning Representation
NP	$\lambda NF.\exists x(N(\mathrm{Base}, x) \wedge F(x))$
$S\backslash NP_{nom}$	$\lambda QK.Q(\lambda I.I, \lambda x.\exists v(K(\mathrm{Base}, v) \wedge (Nom(v) = x)))$
$S\backslash NP_{nom}/NP_{acc}$	$\lambda Q_2 Q_1 K.Q_1(\lambda I.I, \lambda x_1.Q_2(\lambda I.I, \lambda x_2.\exists v(K(\mathrm{Base}, v)$ $\wedge (Nom(v) = x_1) \wedge (Acc(v) = x_2))))$
S/S	$\lambda SK.S(\lambda Jv.K(\lambda v'.(J(v') \wedge \mathrm{Base}(v')), v))$
NP/NP	$\lambda QNF.Q(\lambda Gx.N(\lambda y.(\mathrm{Base}(y) \wedge G(y)), x), F)$

Types

$$\text{Type} \ ::= \ \mathtt{E} \mid \mathtt{Event} \mid \mathtt{T} \mid \mathrm{X} \Rightarrow \mathrm{Y}$$

Mapping from syntactic categories to semantic types

$$\begin{aligned}
NP^{\bullet} &= ((\mathtt{E} \to \mathtt{T}) \to \mathtt{E} \to \mathtt{T}) \to (\mathtt{E} \to \mathtt{T}) \to \mathtt{T} \\
S^{\bullet} &= ((\mathtt{Event} \to \mathtt{T}) \to \mathtt{Event} \to \mathtt{T}) \to \mathtt{T} \\
(C1/C2)^{\bullet} &= (C1\backslash C2)^{\bullet} = C2^{\bullet} \to C1^{\bullet}
\end{aligned}$$

English CCG parser

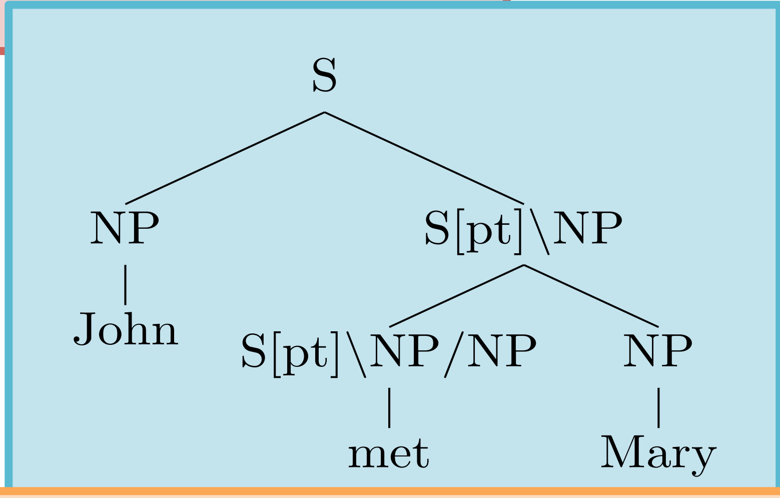
✓ **Penn Treebank**

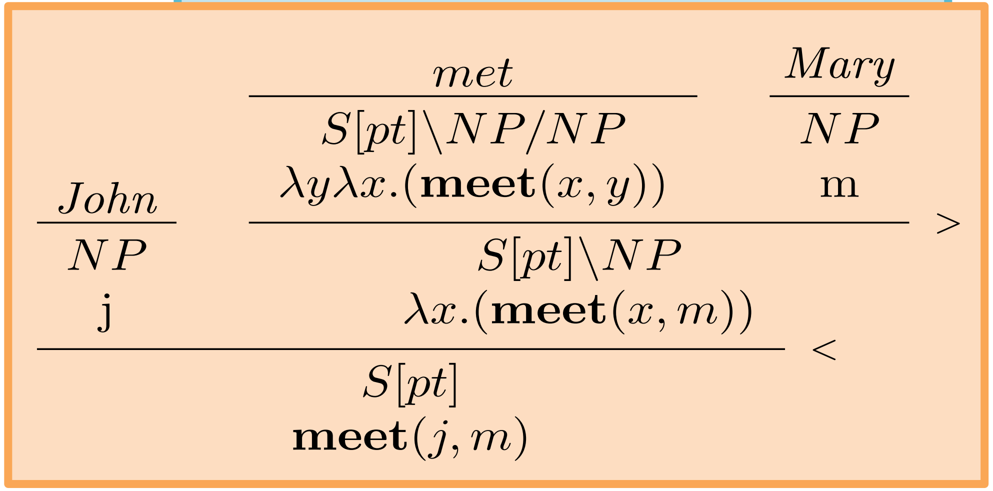
✓ **CCGBank**
[Hockenmaier and Steedman 2007]

✓ **CCG parser**
- **C&C** [Curran and Clark 2007]
- **EasyCCG** [Lewis and Steedman EMNLP2014]
- **depccg** [Yoshikawa+ ACL2017]

✓ **Semantic Parser**
- **Boxer** [Bos+ 2004]
- **Langpro** [Abzianidze EMNLP2015]
- **ccg2lambda** [Mineshima+ EMNLP2015]

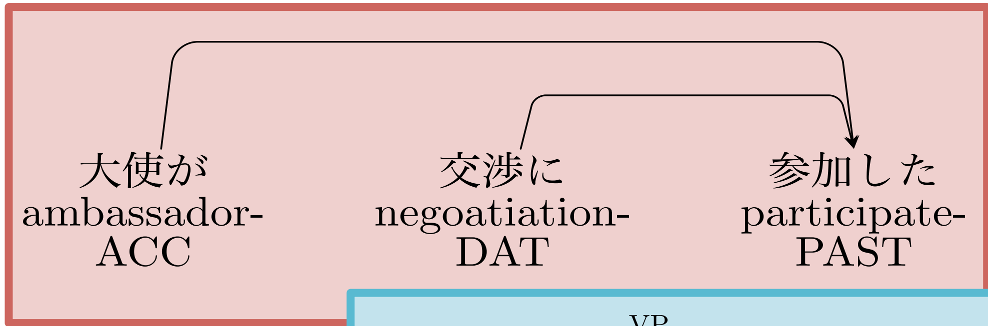
```
(S (NP-SBJ-1 John)
   (VP (VBN met)
       (NP Mary)))
```

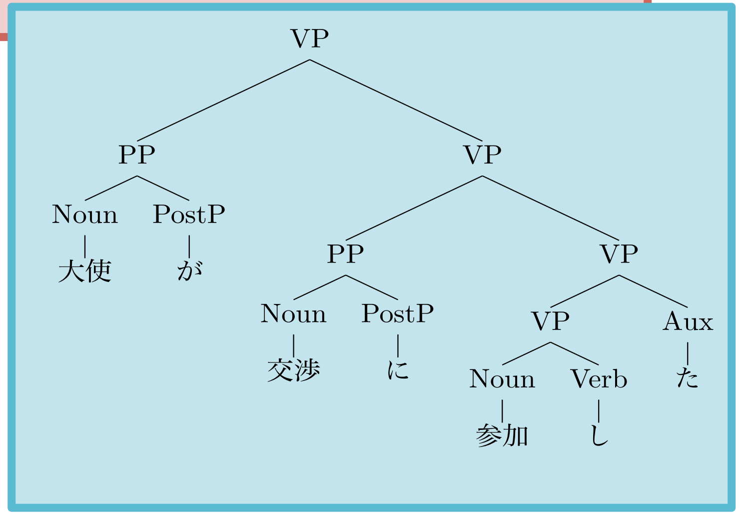




Japanese CCG parser

- ✓ **Kyoto/NAIST Corpus**
- ✓ **Japanese CCGBank**
  [Uematsu+ ACL2013]
- ✓ **CCG parser (Jigg, depccg)**
  - **Jigg** [Noji and Miyao ACL2016]
  - **depccg** [Yoshikawa+ ACL2017]
- ✓ **Semantic parser (ccg2lambda)**
  - **ccg2lambda** [Mineshima+ EMNLP2016]





Three levels of MRs

- Level 1 : Predicate-Argument structure
- Level 2 : Basic logical features (negation, disjunction, etc.)
- Level 3 : Higher-order logical features

Level 1: Predicate-Argument Structure

- Who did what, where, when?
- MRs in Event semantics (Parsons, 1990):

Brutus stabbed Caesar on the street at noon.

$$\exists e(\mathit{stab}(e) \wedge (\mathit{subj}(e) = \mathit{brutus}) \wedge (\mathit{obj}(e) = \mathit{caesar}) \wedge (\mathit{location}(e) = \mathit{street}) \wedge (\mathit{time}(e) = \mathit{noon}))$$

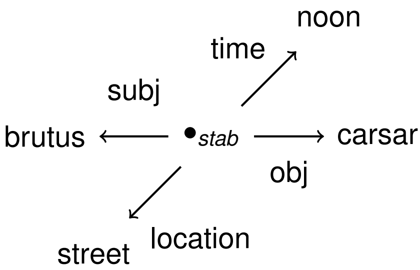
- MRs have a flat structure with:
  - $\exists$ (existential quantifier)
  - $\wedge$ (conjunction)
- Extensional descriptions of scenes or situations

Other notations: DRS and Graph

- Discourse Representation Structure (DRS) (Kamp and Reyle, 1993):

e
stab(e) subj(e) = brutus obj(e) = caesar location(e) = street time(e) = noon

- Graph notation:



- These three notations deliver the same information

The Diamond Inference

(1) Brutus stabbed Caesar on the street at noon.

$\Rightarrow$ (2) Brutus stabbed Caesar on the street

$\Rightarrow$ (3) Brutus stabbed Caesar at noon.

$\Rightarrow$ (4) Brutus stabbed Caesar.

$$\begin{tikzcd}
& (1) \arrow[dl] \arrow[dr] & \\
(2) \arrow[dr] & & (3) \arrow[dl] \\
& (4) &
\end{tikzcd}$$

e
stab(e) subj(e) = brutus obj(e) = caesar location(e) = street time(e) = noon

The Diamond Inference

(1) Brutus stabbed Caesar on the street at noon.

$\Rightarrow$ (2) Brutus stabbed Caesar on the street

$\Rightarrow$ (3) Brutus stabbed Caesar at noon.

$\Rightarrow$ (4) Brutus stabbed Caesar.

$$
\begin{tikzcd}
 & (1) \arrow[dl] \arrow[dr] & \\
(2) \arrow[dr] & & (3) \arrow[dl] \\
 & (4) &
\end{tikzcd}
$$

e
stab(e) subj(e) = brutus obj(e) = caesar location(e) = street time(e) = noon

The Diamond Inference

(1) Brutus stabbed Caesar on the street at noon.

$\Rightarrow$ (2) Brutus stabbed Caesar on the street

$\Rightarrow$ (3) Brutus stabbed Caesar at noon.

$\Rightarrow$ (4) Brutus stabbed Caesar.

$$\begin{tikzcd} & (1) \arrow[dl] \arrow[dr] & \\ (2) \arrow[dr] & & (3) \arrow[dl] \\ & (4) & \end{tikzcd}$$

e
stab(e)
subj(e) = brutus
obj(e) = caesar
location(e) = street
time(e) = noon

The Diamond Inference

(1) Brutus stabbed Caesar on the street at noon.

$\Rightarrow$ (2) Brutus stabbed Caesar on the street

$\Rightarrow$ (3) Brutus stabbed Caesar at noon.

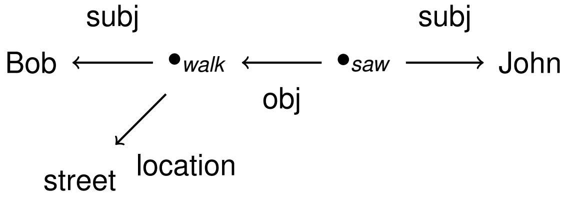
$\Rightarrow$ (4) Brutus stabbed Caesar.

$$\begin{tikzcd}
 & (1) \arrow[dl] \arrow[dr] & \\
(2) \arrow[dr] & & (3) \arrow[dl] \\
 & (4) &
\end{tikzcd}$$

e
stab(e)
subj(e) = brutus
obj(e) = caesar
location(e) = street
time(e) = noon

The Semantics of Voice

- Perceptual report:
  John saw Bob walking on the street.
  ⇒ Bob walked on the street.



- Active-Passive alternation:
  Brutus stabbed Caesar.
  ⇒ Caesar was stabbed by Brutus.
- Causative-inchoative alternation:
  John closed the door.
  ⇒ The door became closed.

Level 2: Basic logic features

- Add basic logic features:
  - *not* (negation, $\neg$)
  - *or* (disjunction, $\vee$)
  - *if* (implication, $\rightarrow$)
  - *any* (universal quantification, $\forall$)
- Indeterminate/underspecified description of a situation
- Not easy to visualize ("Draw a picture of *A man is not walking*")

Monotonicity inference

Basic/general patterns of inferences triggered by logic features

P entails *H*

$=$ There is no situation in which *P* is true but *H* is false.

$=$ The information in *P* already contains the information in *H*.

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence? (Moss 2014)

P: Some bears danced.

H1. Some animals danced.
H2. Some grizzlies danced.
H3. Some bears moved.
H4. Some bears waltzed.

Monotonicity inference

Basic/general patterns of inferences triggered by logic features

P entails *H*

= There is no situation in which *P* is true but *H* is false.

= The information in *P* already contains the information in *H*.

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence? (Moss 2014)

P: Some bears danced.
$\Rightarrow$ H1. Some animals danced.
H2. Some grizzlies danced.
H3. Some bears moved.
H4. Some bears waltzed.

Monotonicity inference

Basic/general patterns of inferences triggered by logic features

P entails *H*

$=$ There is no situation in which *P* is true but *H* is false.

$=$ The information in *P* already contains the information in *H*.

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence? (Moss 2014)

P: Some bears danced.
$\Rightarrow$ H1. Some animals danced.
$\not\Rightarrow$ H2. Some grizzlies danced.
H3. Some bears moved.
H4. Some bears waltzed.

Monotonicity inference

Basic/general patterns of inferences triggered by logic features

P entails H

$=$ There is no situation in which P is true but H is false.

$=$ The information in P already contains the information in H.

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence? (Moss 2014)

P: Some bears danced.
$\Rightarrow$ H1. Some animals danced.
$\not\Rightarrow$ H2. Some grizzlies danced.
$\Rightarrow$ H3. Some bears moved.
H4. Some bears waltzed.

Monotonicity inference

Basic/general patterns of inferences triggered by logic features

P entails *H*

$=$ There is no situation in which *P* is true but *H* is false.

$=$ The information in *P* already contains the information in *H*.

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence? (Moss 2014)

P: Some bears danced.
$\Rightarrow$ H1. Some animals danced.
$\not\Rightarrow$ H2. Some grizzlies danced.
$\Rightarrow$ H3. Some bears moved.
$\not\Rightarrow$ H4. Some bears waltzed.

Monotonicity inference

Basic/general patterns of inferences triggered by logic features

P entails *H*

$=$ There is no situation in which *P* is true but *H* is false.

$=$ The information in *P* already contains the information in *H*.

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence? (Moss 2014)

P: Some bears danced.
$\Rightarrow$ H1. Some animals danced.
$\not\Rightarrow$ H2. Some grizzlies danced.
$\Rightarrow$ H3. Some bears moved.
$\not\Rightarrow$ H4. Some bears waltzed.

We write: Some bears$^{\uparrow}$ danced$^{\uparrow}$

NP and *VP* in *Some NP VP* are upward monotonic

Monotonicity inference

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence?

P: No bears danced.

H1. No animals danced.

H2. No grizzlies danced.

H3. No bears moved.

H4. No bears waltzed.

Monotonicity inference

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence?

P: No bears danced.

$\not\Rightarrow$ H1. No animals danced.

H2. No grizzlies danced.

H3. No bears moved.

H4. No bears waltzed.

Monotonicity inference

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence?

P: No bears danced.
$\not\Rightarrow$ H1. No animals danced.
$\Rightarrow$ H2. No grizzlies danced.
H3. No bears moved.
H4. No bears waltzed.

Monotonicity inference

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence?

P: No bears danced.
$\not\Rightarrow$ H1. No animals danced.
$\Rightarrow$ H2. No grizzlies danced.
$\not\Rightarrow$ H3. No bears moved.
H4. No bears waltzed.

Monotonicity inference

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence?

P: No bears danced.
$\not\Rightarrow$ H1. No animals danced.
$\Rightarrow$ H2. No grizzlies danced.
$\not\Rightarrow$ H3. No bears moved.
$\Rightarrow$ H4. No bears waltzed.

Monotonicity inference

- *grizzly* $\leq$ *bear* $\leq$ *animal*
- *waltz* $\leq$ *dance* $\leq$ *move*

P entails which sentence?

P: No bears danced.
$\not\Rightarrow$ H1. No animals danced.
$\Rightarrow$ H2. No grizzlies danced.
$\not\Rightarrow$ H3. No bears moved.
$\Rightarrow$ H4. No bears waltzed.

We write: No bears$^{\downarrow}$ danced$^{\downarrow}$
NP and *VP* in *No NP VP* are downward monotonic

- Logical words like *some*, *no*, *every*, *any*, *not*, *if* play a role in determining the upward/downward monotonicity.

Bare NPs

For bare NPs (NPs without determines), predicates play a crucial role.

$tigress \leq tiger \leq animal$

Tigers are striped. 虎には縞模様がある
$\Rightarrow$ Tigresses are striped. 雌の虎には縞模様がある
$\not\Rightarrow$ Animals are striped. 動物には縞模様がある

Tigers are on the lawn. 虎が芝生の上にいる
$\not\Rightarrow$ Tigresses are on the lawn. 雌の虎が芝生の上にいる
$\Rightarrow$ Animals are on the lawn. 動物が芝生の上にいる

Tigers$^{\downarrow}$ are striped. (individual-level predicate)
Tigers$^{\uparrow}$ are on the lawn. (stage-level predicate)

- All the basic patterns of monotonicity inferences are directly predictable from logic-based MRs (eg. FOL).

Level 3: Advanced logic features

There are many linguistic phenomena that allegedly go beyond first-order logic.

- Attitudes, modals and aspectual operators.
- Generalized/proportional quantifiers
- Intensional adjectives
- Comparative and superlatives
- Other higher-order predicates

Some features:

- Introducing intensionality (involving speaker's perspectives, mental states, etc.)
- Quantifying over higher-order objects (objects other than entities)
- Not directly formalizable in first-order logics

Attitudes, modals and temporal operators

- Attitude predicates like *know* and *believe* take propositional objects as argument.
- Inferential contrast between factive predicates (eg. know) and non-factive predicate (eg. believe)

- John knows that it is raining.
  $\Rightarrow$ It is raining.
- John does not know that it is raining.
  $\Rightarrow$ It is raining.
- John believes that it is raining.
  $\not\Rightarrow$ It is raining.
- John does not believe that it is raining.
  $\not\Rightarrow$ It is raining.

- modals: *likely*, *probably*, *might*, *must*, *can*. etc.
- aspectual operators: progressives, perfectives, etc.

Generalized quantifiers

- *Most*, *half of*, *70% of* ...

Most students smoked.	$\not\Rightarrow \not\Leftarrow$	Most female student smoked.
Most students smoked.	$\Longleftarrow$	Most student smoked in a building.

- But these quantifiers are known to be not first-orderizable (Barwise and Cooper, 1981)

Adjectives: subsective and non-subsective

Subsective (intersective) adjective

- Dumbo is a small elephant.
  $\Rightarrow$ Dumbo is an elephant.

Non-subsective adjective

- This is a fake diamond.
  $\not\Rightarrow$ This is a diamond.
  $\Rightarrow$ This is not a diamond.

Comparatives

- Alice is taller than Bob.
  $\not\Rightarrow$ Alice is tall.

- Alice is taller than Bob.
- Bob is tall.
  $\Rightarrow$ Alice is tall.

- Alice is taller than Bob.
- Bob is taller than Carol.
  $\Rightarrow$ Alice is taller than Carol.

Question:

- What are proper MRs for adjective constructions that are suitable to efficient inferences?
- How to give a compositional semantics of predicates *tall* and *taller* (how the meanings of *tall* and *taller* are related each other?)

Some higher-order predicates

- Higher-order predicates that apply to objects other than entities: *rise*, *change*, *decrease*

- The price of gasoline is rising.
- The price of gasoline is 1,000 dollars.

  $\not\Rightarrow$ 1,000 dollars are rising.

Logic-based Meaning Representations

Natural Logic

- formalizes inferences with surface form
- ▲ only allows single premise inferences (mononicity inference)

more efficient
less expressive

MacCartney (2009)

First-order logic (FOL)

- efficient provers exist
- dominate computational linguistics
- ▲ limited expressive power

Boxer (Bos 2008)

Higher-order logic (HOL)

- high expressive power
- dominate formal semantics
- ▲ no general-purpose efficient prover exists

less efficient
more expressive

Mineshima et al. (2015)

Logic-based Meaning Representations

Natural Logic	First-order logic (FOL)	Higher-order logic (HOL)
● formalizes inferences with surface form ▲ only allows single premise inferences (mononicity inference)	● efficient provers exist ● dominate computational linguistics ▲ limited expressive power	● high expressive power ● dominate formal semantics ▲ no general-purpose efficient prover exists
more efficient less expressive	⟷	less efficient more expressive
MacCartney (2009)	Boxer (Bos 2008)	Mineshima et al. (2015)

Logic-based Meaning Representations

Natural Logic

- formalizes inferences with surface form
- ▲ only allows single premise inferences (mononicity inference)

more efficient
less expressive

MacCartney (2009)

First-order logic (FOL)

- efficient provers exist
- dominate computational linguistics
- ▲ limited expressive power

Boxer (Bos 2008)

Higher-order logic (HOL)

- high expressive power
- dominate formal semantics
- ▲ no general-purpose efficient prover exists

less efficient
more expressive

Mineshima et al. (2015)

HOL as representation language

Higher-order constructions in natural languages

1. Generalized quantifiers
   Most students work $\rightsquigarrow$ $most(\lambda.student(x), \lambda x.work(x))$
2. Modals
   John might come $\rightsquigarrow$ $might(come(j))$
3. Veridical and anti-veridical predicates
   Someone managed to come $\rightsquigarrow$ $\exists x(manage(x, come(x)))$
   Someone failed to come $\rightsquigarrow$ $\exists x(fail(x, come(x)))$
4. Attitude verbs
   John knows that some student came. $\rightsquigarrow$
   $$know(j, \exists x(student(x) \wedge come(x)))$$

- Alternative: first-order decomposition/reification (Hobbs, 1985)

Natural Language Inference (Recognizing Textual Entailment, RTE)

- Does P entail H?

P Most cities in Japan prohibit smoking in restaurants.
H Some cities in Japan do not allow smoking in public spaces.

Yes (entail)

- *The best way of testing an NLP system's semantic capacity* (Cooper et al. 1996)
- Many applications in NLP
  - Question Answering,
  - Text Summarization
  - Fact validation/checking
  - etc.

Datasets for Recognizing Textual Entailment (RTE)

- English:

Dataset	Size	Crowdsourcing
FraCaS (Cooper et al., 1994)	346	
PASCAL-RTE1–5 (Dagan et al. 2006)	7K	
SICK (Marelli et al., 2014)	10K	$\surd$
SNLI (Bowman et al., 2015)	570K	$\surd$
MultiNLI (Williams et al. 2017)	432K	$\surd$

- Japanese:

Dataset	Size	Crowdsourcing
JSeM	780	
NTCIR RITE 1–2	1,800	
Kyoto RTE dataset	2,471	

FraCaS (Cooper et al. 1996)

- Created by linguists in 1990s.
- Size: 346 problems
- The inferences are divided into nine sections in terms of major semantic phenomena:
  - Generalized quantifier, Plurals, Nominal anaphora, Ellipsis, Adjective, Comparatives, Temporal reference, Verbs, Attitudes
- Contains lots of logical expression (at Level 2 and Level 3)
- Lexical and world knowledge is mostly excluded
- Contains multiple-premise inferences

# premise	# problem	
1	192	55.5%
2	122	35.3%
3	29	8.4%
4	2	0.6%
5	1	0.3%

FraCaS: Examples

- The XML format was created by Bill MacCartney
  `https://nlp.stanford.edu/w̃cmac/downloads/`

fracas-038 (Generalized quantifier) label: no (contradiction)
P: No delegate finished the report.
H: Some delegate finished the report on time.

fracas-084 (Plural) label: yes (entailment)
P: Either Smith, Jones or Anderson signed the contract.
H: If Smith and Anderson did not sign the contract, Jones signed the contract.

fracas-134 (Nominal Anaphora) label: yes (entailment)
P1: Every customer who owns a computer has a service contract for it.
P2: MFI is a customer that owns exactly one computer.
H: MFI has a service contract for all its computers.

Japanese Semantics Test Suite (JSeM)

Kawazoe et al (2015)

`http://researchmap.jp/community-inf/JSeM/`

- Translation of FraCaS (624 problems) and Japanese original ones (166 problems)
- Each problem is tagged with:
  - phenomena type (quantifier, adjective, negation, etc.)
  - inference type (logical entailment, presupposition)
- single-premised (66%) and multi-premised (34%) problems

jsem-id:1 answer: yes inference type: entailment phenomena: Generalized Quantifier, conservativity
linked to: fracas-001 literal translation?: yes same phenomena?: unknown

P1

script あるイタリア人が世界最高のテノール歌手になった。

English An Italian became the world's greatest tenor.

H

script 世界最高のテノール歌手になったイタリア人がいた。

English There was an Italian who became the world's greatest tenor.

SICK (Sentences Involving Compositional Knowldedge)

SemEval14, Marelli et al. (2013)

- Size: $4,500/500/4,927$ for training, dev. and testing.
- Premise: taken from image captions in Flickr30k Corpus
- Hyphothesis and Label: crowdsourcing and expert-check
- contains only single-premise inferences
- contains logical expressions at Level 2 (negation, disjunction, quantifiers)
- Both word-level and phrase-level paraphrases are required

SICK: Examples

SICK-506 (label: no)
P: A man wearing a dyed black shirt is sitting at the table and laughing.
H: There is no man wearing a shirt dyed black, sitting at the table and laughing.

SICK-718 (label: unknown)
P: A few men in a competition are running outside.
H: A few men are running competitions outside.

SICK-3156 (label: yes)
P: A man is cutting a box.
H: A box is being cut by a man.

SICK-3668 (label: yes)
P: A man is strolling in the rain.
H: A man is walking in the rain.

SNLI (Bowman et al. 2015)

- P: taken from image captions in Flickr30k Corpus
- H and Label: crowdsourcing and expert-check
- contains only single-premise inferences
- sentences are confined to a description of a scene, not containing logical features (limited to Level 1)
- largely limited to simple lexical inferences

label: entailment
P: A white dog with long hair jumps to catch a red and green toy.
H: An animal is jumping to catch an object.

MultiNLI (Williams et al. 2017)

- The Multi-Genre Natural Language Inference (MultiNLI)

genre: Fiction, answer: entailment
P: He turned and saw Jon sleeping in his half-tent.
H: He saw Jon was asleep.

genre: telephone, answer: contradiction
P: someone else noticed it and i said well i guess that's true and it was somewhat melodious in other words it wasn't just you know it was really funny
H: No one noticed and it wasn't funny at all.

- A set of linguistic phenomena tags are assigned to the development set (10K sentences):
  - quantifiers, belief verbs, time terms, conditionals, etc.

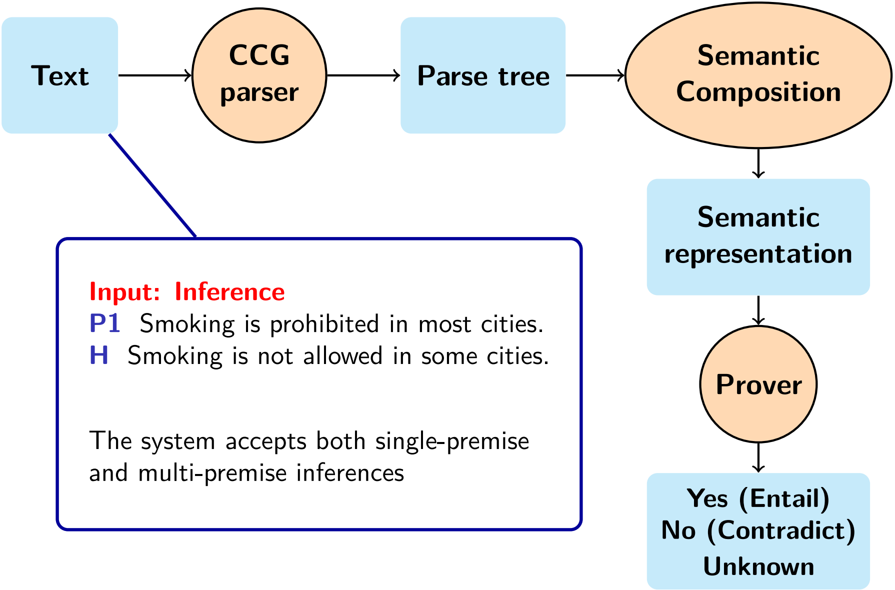
Summary

- Meaning composition via CCG and Lambda Calculus
- Three levels of Meaning Representation: Predicate-Argument Structure, Basic Logics and beyond
- RTE datasets

Introduction to ccg2lambda

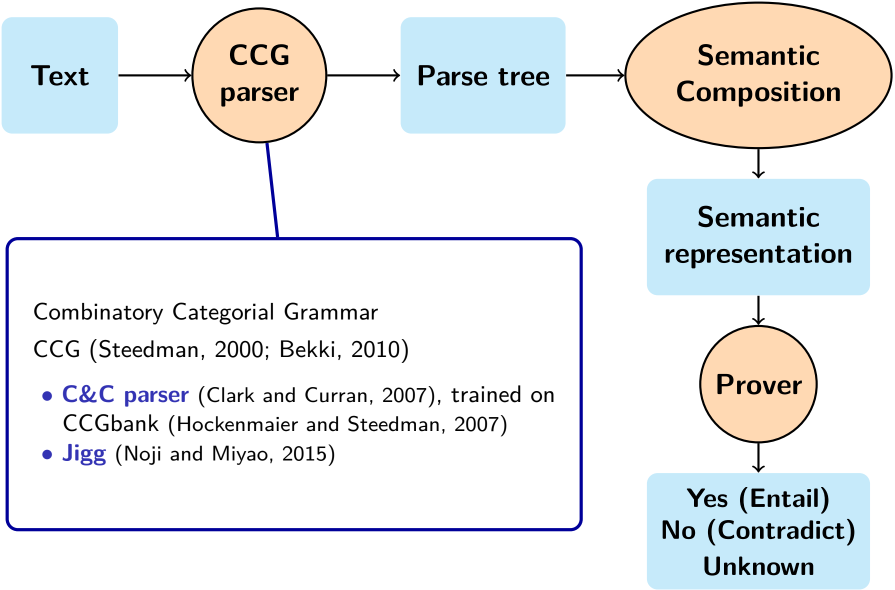
ccg2lambda: Semantic Parser and Inference System

https://github.com/mynlp/ccg2lambda



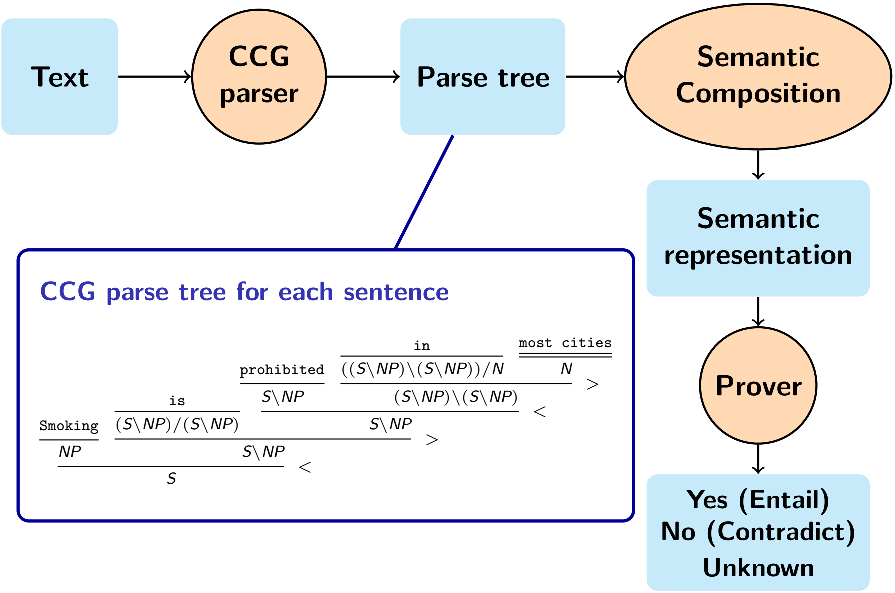
ccg2lambda: Semantic Parser and Inference System

https://github.com/mynlp/ccg2lambda



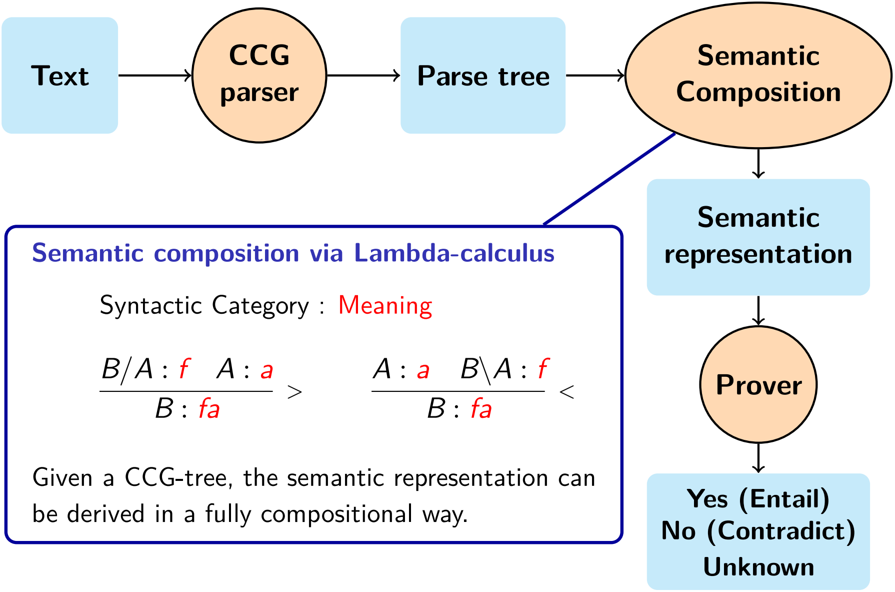
ccg2lambda: Semantic Parser and Inference System

https://github.com/mynlp/ccg2lambda



ccg2lambda: Semantic Parser and Inference System

`https://github.com/mynlp/ccg2lambda`



Semantic composition via Lambda-calculus

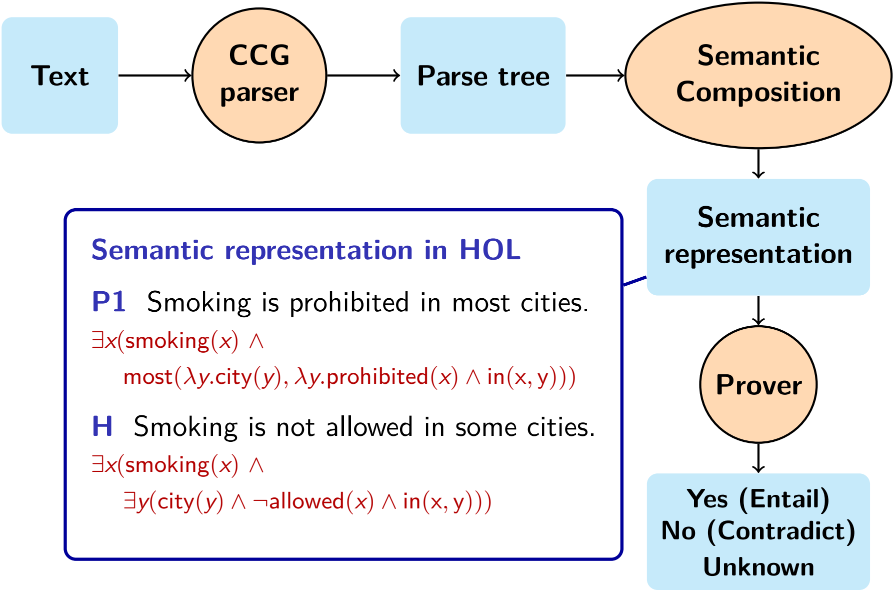
Syntactic Category : Meaning

$$\frac{B/A : f \quad A : a}{B : fa} > \qquad \frac{A : a \quad B\backslash A : f}{B : fa} <$$

Given a CCG-tree, the semantic representation can be derived in a fully compositional way.

ccg2lambda: Semantic Parser and Inference System

`https://github.com/mynlp/ccg2lambda`



Semantic representation in HOL

P1 Smoking is prohibited in most cities.

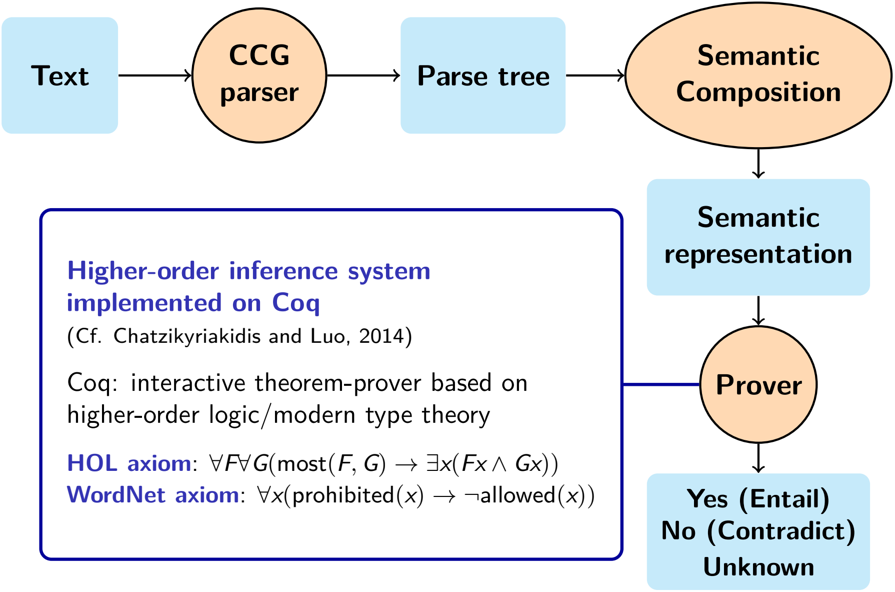
$\exists x(\mathsf{smoking}(x) \wedge$
$\quad \mathsf{most}(\lambda y.\mathsf{city}(y), \lambda y.\mathsf{prohibited}(x) \wedge \mathsf{in}(\mathrm{x}, \mathrm{y})))$

H Smoking is not allowed in some cities.

$\exists x(\mathsf{smoking}(x) \wedge$
$\quad \exists y(\mathsf{city}(y) \wedge \neg\mathsf{allowed}(x) \wedge \mathsf{in}(\mathrm{x}, \mathrm{y})))$

ccg2lambda: Semantic Parser and Inference System

https://github.com/mynlp/ccg2lambda



Higher-order inference system implemented on Coq

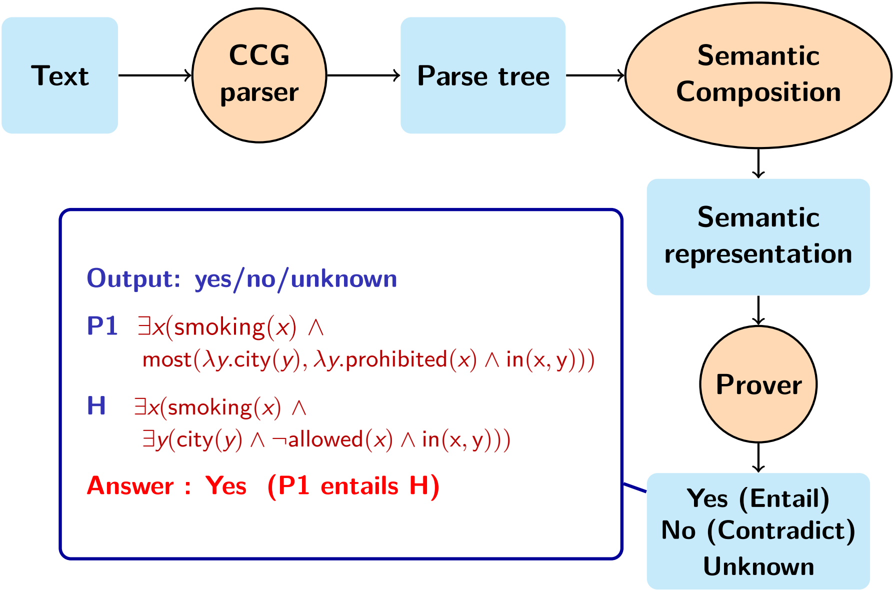
(Cf. Chatzikyriakidis and Luo, 2014)

Coq: interactive theorem-prover based on higher-order logic/modern type theory

HOL axiom: $\forall F \forall G(\mathrm{most}(F, G) \rightarrow \exists x(Fx \wedge Gx))$
WordNet axiom: $\forall x(\mathrm{prohibited}(x) \rightarrow \neg \mathrm{allowed}(x))$

ccg2lambda: Semantic Parser and Inference System

https://github.com/mynlp/ccg2lambda



Output: yes/no/unknown

P1 $\exists x(\mathrm{smoking}(x) \wedge$
$\mathrm{most}(\lambda y.\mathrm{city}(y), \lambda y.\mathrm{prohibited}(x) \wedge \mathrm{in}(\mathrm{x}, \mathrm{y})))$

H $\exists x(\mathrm{smoking}(x) \wedge$
$\exists y(\mathrm{city}(y) \wedge \neg\mathrm{allowed}(x) \wedge \mathrm{in}(\mathrm{x}, \mathrm{y})))$

Answer : Yes (P1 entails H)

Semantic composition on CCG tree

$$
\begin{array}{cccc}
\text{Every} & \text{student} & \text{who} & \text{works} \\
NP/N & N & (NP\backslash NP)/(S\backslash NP) & S\backslash NP \\
\hline
\multicolumn{2}{c}{NP \quad >} & \multicolumn{2}{c}{NP\backslash NP \quad >} \\
\hline
\multicolumn{4}{c}{NP \quad <}
\end{array}
\qquad
\begin{array}{c}
\text{comes} \\
S\backslash NP
\end{array}
$$

$$
\begin{array}{c}
\hline
S
\end{array}
$$

- Syntactic categories and rules indicate composition.

Semantic composition on CCG tree

$$\dfrac{\dfrac{\dfrac{\overset{\text{Every}}{NP/N} \qquad \overset{\text{student}}{\underset{(\lambda Ex.E(x))(\text{student})}{N}}}{NP}> \qquad \dfrac{\overset{\text{who}}{(NP\backslash NP)/(S\backslash NP)} \qquad \overset{\text{works}}{S\backslash NP}}{NP\backslash NP}>}{NP}< \qquad \overset{\text{comes}}{S\backslash NP}}{S}$$

- Syntactic categories and rules indicate composition.
- Open words: schematic lexical entries match syntactic categories.

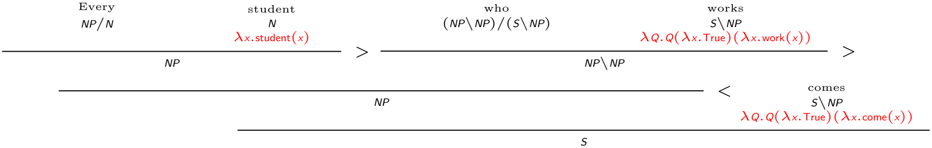
Semantic composition on CCG tree

Every NP/N student N $\color{red}{\lambda x.\mathsf{student}(x)}$ who $(NP\backslash NP)/(S\backslash NP)$ works $S\backslash NP$

$$\dfrac{\dfrac{\dfrac{\text{Every}\ NP/N \quad \text{student}\ N\ \lambda x.\mathsf{student}(x)}{NP}> \quad \dfrac{\text{who}\ (NP\backslash NP)/(S\backslash NP) \quad \text{works}\ S\backslash NP}{NP\backslash NP}>}{NP}< \quad \text{comes}\ S\backslash NP}{S}$$

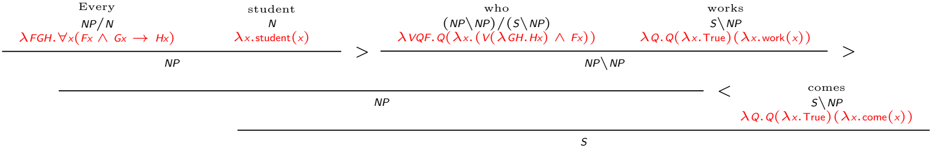
- Syntactic categories and rules indicate composition.
- Open words: schematic lexical entries match syntactic categories.
- β-reduction with lemmas as arguments.

Semantic composition on CCG tree



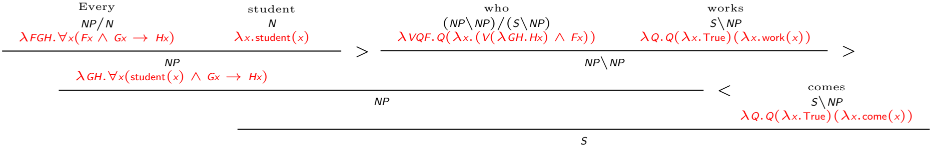
- Syntactic categories and rules indicate composition.
- Open words: schematic lexical entries match syntactic categories.
- β-reduction with lemmas as arguments.
- Semantics more interesting for verbs.

Semantic composition on CCG tree



- Syntactic categories and rules indicate composition.
- Open words: schematic lexical entries match syntactic categories.
- β-reduction with lemmas as arguments.
- Semantics more interesting for verbs.
- Closed words: direct assignment.

Semantic composition on CCG tree



- Syntactic categories and rules indicate composition.
- Open words: schematic lexical entries match syntactic categories.
- β-reduction with lemmas as arguments.
- Semantics more interesting for verbs.
- Closed words: direct assignment.
- Semantic composition from leaves to root.

Semantic composition on CCG tree

$$\dfrac{\dfrac{\underset{\lambda FGH.\forall x(Fx \wedge Gx \rightarrow Hx)}{\underset{NP/N}{\text{Every}}} \quad \underset{\lambda x.\mathsf{student}(x)}{\underset{N}{\text{student}}}}{\underset{\lambda GH.\forall x(\mathsf{student}(x) \wedge Gx \rightarrow Hx)}{NP}}> \quad \dfrac{\underset{\lambda VQF.Q(\lambda x.(V(\lambda GH.Hx) \wedge Fx))}{\underset{(NP\backslash NP)/(S\backslash NP)}{\text{who}}} \quad \underset{\lambda Q.Q(\lambda x.\mathsf{True})(\lambda x.\mathsf{work}(x))}{\underset{S\backslash NP}{\text{works}}}}{\underset{\lambda QF.Q(\lambda x.(\mathsf{work}(x) \wedge Fx))}{NP\backslash NP}}>}{\underset{\lambda FH.\forall x(\mathsf{student}(x) \wedge \mathsf{work}(x) \wedge Fx \rightarrow Hx)}{NP}}<$$

$$\dfrac{\underset{\lambda FH.\forall x(\mathsf{student}(x) \wedge \mathsf{work}(x) \wedge Fx \rightarrow Hx)}{NP} \quad \underset{\lambda Q.Q(\lambda x.\mathsf{True})(\lambda x.\mathsf{come}(x))}{\underset{S\backslash NP}{\text{comes}}}}{\underset{\forall x(\mathsf{student}(x) \wedge \mathsf{work}(x) \wedge \mathsf{True} \rightarrow \mathsf{come}(x))}{S}}$$

- Syntactic categories and rules indicate composition.
- Open words: schematic lexical entries match syntactic categories.
- β-reduction with lemmas as arguments.
- Semantics more interesting for verbs.
- Closed words: direct assignment.
- Semantic composition from leaves to root.
- Logical meaning representation of the sentence at the root.

Lexical entries

1. For **closed words**: lexical entries directly assigned to surface form (a limited number of grammatical and logical expressions): 80 entries

Example

- **category**: NP/N
- **semantics**: $\lambda F \lambda G \lambda H. \forall x (Fx \wedge Gx \rightarrow H)$
- **surf**: every

2. For **open words**: schematic lexical entry (semantic templates) assigned to syntactic categories: 57 entries

Example

- **category**: N
- **semantics**: $\lambda E \lambda x.\mathrm{E}(x)$

"E" is a position in which a particular lexical item appears.

ccg2lambda: a few more words

https://github.com/mynlp/ccg2lambda

- Publicly available and open-sourced.
- Easy to use (simple programs):

ccg2lambda: a few more words

https://github.com/mynlp/ccg2lambda

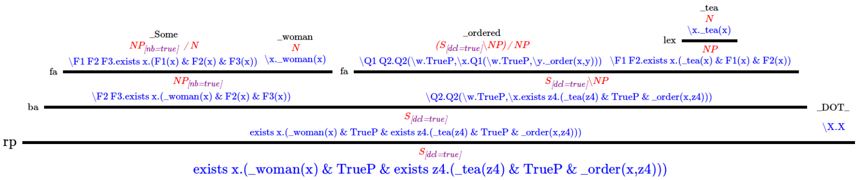
- Publicly available and open-sourced.
- Easy to use (simple programs):
  - `# python semparse.py ccgtrees.xml templates.yaml semantics.xml`

```xml
<?xml version='1.0' encoding='utf-8'?>
<root>
  <document>
    <sentences>
      <sentence>
        <tokens>
          <token id="t0_0" pos="DT"  cat="NP[nb]/N"      surf="Some"    base="some"/>
          <token id="t0_1" pos="NN"  cat="N"             surf="woman"   base="woman"/>
          <.../>
        </tokens>
        <ccg root="s0_sp0" id="s0_ccg0">
          <span id="s0_sp0" child="s0_sp1 s0_sp9" category="S[dcl=true]"         rule="rp"/>
          <span id="s0_sp1" child="s0_sp2 s0_sp5" category="S[dcl=true]"         rule="ba"/>
          <...>
        </ccg>
        <semantics status="success" root="s0_sp0">
          <span id="s0_sp0" child="s0_sp1 s0_sp9"
                sem="exists x.(_woman(x) & TrueP & exists z1.(_tea(z1) & TrueP & _order(x,z1)))"/>
          <span id="s0_sp4" type="_woman : Entity -> Prop"
                sem="\x._woman(x)"/>
          <...>
        </semantics>
      </sentence>
    </sentences>
  </document>
</root>
```

ccg2lambda: a few more words

https://github.com/mynlp/ccg2lambda

- Publicly available and open-sourced.
- Easy to use (simple programs):
  - `# python semparse.py ccgtrees.xml templates.yaml semantics.xml`
  - `# python visualize.py semantics.xml > semantics.html`



ccg2lambda: a few more words

https://github.com/mynlp/ccg2lambda

- Publicly available and open-sourced.
- Easy to use (simple programs):
  - `# python semparse.py ccgtrees.xml templates.yaml semantics.xml`
  - `# python visualize.py semantics.xml > semantics.html`
  - `# python prove.py semantics.xml`

ccg2lambda: a few more words

https://github.com/mynlp/ccg2lambda

- Publicly available and open-sourced.
- Easy to use (simple programs):
  - `# python semparse.py ccgtrees.xml templates.yaml semantics.xml`
  - `# python visualize.py semantics.xml > semantics.html`
  - `# python prove.py semantics.xml`
- Easy to extend (declarative).

$$
\begin{aligned}
&- \texttt{semantics} : \lambda\text{-formula} \\
&\quad \texttt{category} : \mathrm{syntactic\_category} \\
&\quad \texttt{cond}_2 : \mathrm{value}_2 \\
&\quad \texttt{cond}_i : \mathrm{value}_i
\end{aligned}
$$

ccg2lambda: a few more words

https://github.com/mynlp/ccg2lambda

- Publicly available and open-sourced.
- Easy to use (simple programs):
  - `# python semparse.py ccgtrees.xml templates.yaml semantics.xml`
  - `# python visualize.py semantics.xml > semantics.html`
  - `# python prove.py semantics.xml`
- Easy to extend (declarative).
- Easy to process (XML output).

Recognizing Textual Entailment

Recognizing Textual Entailment

- Does **Premise P** entail **Hypothesis H**?

P Smoking in restaurants is prohibited by law in most cities in Japan.
H Smoking in public spaces is not allowed in some cities.

Yes (Entailment)

Recognizing Textual Entailment

- Does **Premise P** entail **Hypothesis H**?

P Smoking in restaurants is prohibited by law in most cities in Japan.
H Smoking in public spaces is not allowed in some cities.

Yes (Entailment)

- *The best way of testing an NLP system's semantic capacity* (Cooper et al. 1996)
- Many application areas (Question Answering, Machine Translation, etc.)

Recognizing Textual Entailment

- Does **Premise P** entail **Hypothesis H**?

P Smoking in restaurants is prohibited by law in most cities in Japan.
H Smoking in public spaces is not allowed in some cities.

Yes (Entailment)

- *The best way of testing an NLP system's semantic capacity* (Cooper et al. 1996)
- Many application areas (Question Answering, Machine Translation, etc.)

- relevant factors:
  1. syntax
  2. logical words: *most, not, some, every*

Logical/ Compositional semantics

Recognizing Textual Entailment

- Does **Premise P** entail **Hypothesis H**?

P Smoking in restaurants is prohibited by law in most cities in Japan.
H Smoking in public spaces is not allowed in some cities.

Yes (Entailment)

- *The best way of testing an NLP system's semantic capacity* (Cooper et al. 1996)
- Many application areas (Question Answering, Machine Translation, etc.)

- relevant factors:

1. syntax
2. logical words: *most*, *not*, *some*, *every*

Logical/ Compositional semantics

3. content words:
restaurant $\rightarrow$ *public_space*
prohibited $\rightarrow$ $\neg$ *allowed*

Lexical Knowledge

Introducing Lexical Knowledge

Introduction

Logic sometimes is not enough

T: *men are sawing logs.*

$$\exists x.(\mathrm{man}(x) \to \exists y.(\mathrm{log}(y) \wedge \mathrm{saw}(x, y))$$

H: *men are cutting wood.*

$$\exists x.(\mathrm{man}(x) \to \exists y.(\mathrm{wood}(y) \wedge \mathrm{cut}(x, y))$$

Introduction

Logic sometimes is not enough

T: *men are sawing logs.*

$$\exists x.(\mathrm{man}(x) \rightarrow \exists y.(\mathrm{log}(y) \wedge \mathrm{saw}(x, y))$$

H: *men are cutting wood.*

$$\exists x.(\mathrm{man}(x) \rightarrow \exists y.(\mathrm{wood}(y) \wedge \mathrm{cut}(x, y))$$

Method: to inject lexical knowledge into the proof.

- Word relations can be found in ontologies (e.g. WordNet, etc.)

$$\forall x \forall y.\mathrm{saw}(x, y) \rightarrow \mathrm{cut}(x, y)$$

$$\forall x.\mathrm{log}(x) \rightarrow \mathrm{wood}(x)$$

Naïve injection of lexical knowlege

Running example:

$$\exists x_1 v_1 (\mathsf{dog}(x_1) \wedge \mathsf{white}(x_1) \wedge \mathsf{black}(x_1) \wedge \mathsf{nap}(v_1) \wedge \mathsf{Subj}(v_1) = x_1)$$

T: A black and white dog naps .

H: A black and white dog sleeps .

$$\exists x_2 v_2 (\mathsf{dog}(x_2) \wedge \mathsf{white}(x_2) \wedge \mathsf{black}(x_2) \wedge \mathsf{sleep}(v_2) \wedge \mathsf{Subj}(v_2) = x_2)$$

- Obtain semantic representation.

Naïve injection of lexical knowlege

Running example:

$$\exists x_1 v_1 (\mathsf{dog}(x_1) \wedge \mathsf{white}(x_1) \wedge \mathsf{black}(x_1) \wedge \mathsf{nap}(v_1) \wedge \mathsf{Subj}(v_1) = x_1)$$

T: *A black and white dog naps.*

H: *A black and white dog sleeps.*

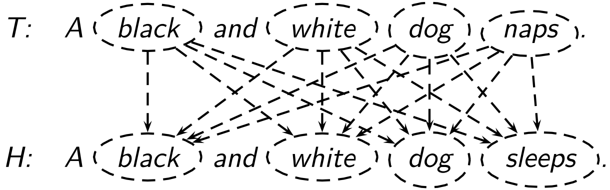
$$\exists x_2 v_2 (\mathsf{dog}(x_2) \wedge \mathsf{white}(x_2) \wedge \mathsf{black}(x_2) \wedge \mathsf{sleep}(v_2) \wedge \mathsf{Subj}(v_2) = x_2)$$

- Identify content/interesting words.

Naïve injection of lexical knowlege

Running example:

$$\exists x_1 v_1(\mathsf{dog}(x_1) \wedge \mathsf{white}(x_1) \wedge \mathsf{black}(x_1) \wedge \mathsf{nap}(v_1) \wedge \mathsf{Subj}(v_1) = x_1)$$



$$\exists x_2 v_2(\mathsf{dog}(x_2) \wedge \mathsf{white}(x_2) \wedge \mathsf{black}(x_2) \wedge \mathsf{sleep}(v_2) \wedge \mathsf{Subj}(v_2) = x_2)$$

- Enumerate possible relations.

Naïve injection of lexical knowlege

Running example:

$$\exists x_1 v_1 (\text{dog}(x_1) \wedge \text{white}(x_1) \wedge \text{black}(x_1) \wedge \text{nap}(v_1) \wedge \text{Subj}(v_1) = x_1)$$

T: *A black and white dog naps.*

H: *A black and white dog sleeps.*

$$\exists x_2 v_2 (\text{dog}(x_2) \wedge \text{white}(x_2) \wedge \text{black}(x_2) \wedge \text{sleep}(v_2) \wedge \text{Subj}(v_2) = x_2)$$

- Select/predict relations according to ontology or classifier:
  - $\forall x.\text{black}(x) \rightarrow \neg\ \text{white}(x)$
  - $\forall x.\text{white}(x) \rightarrow \neg\ \text{black}(x)$
  - $\forall v.\text{nap}(v) \rightarrow \text{sleep}(v)$

Naïve injection of lexical knowlege

Running example:

$$\exists x_1 v_1(\mathsf{dog}(x_1) \wedge \mathsf{white}(x_1) \wedge \mathsf{black}(x_1) \wedge \mathsf{nap}(v_1) \wedge \mathsf{Subj}(v_1) = x_1)$$

T: *A black and white dog naps.*

H: *A black and white dog sleeps.*

$$\exists x_2 v_2(\mathsf{dog}(x_2) \wedge \mathsf{white}(x_2) \wedge \mathsf{black}(x_2) \wedge \mathsf{sleep}(v_2) \wedge \mathsf{Subj}(v_2) = x_2)$$

- Insert knowledge, run proof.
  - ... *and possibly get the wrong answer.*
  - This problem is aggravated for longer sentences.

Proving strategy and Axiom construction

$T : \exists x_1 v_1 (\text{dog}(x_1) \wedge \text{white}(x_1) \wedge \text{black}(x_1) \wedge \text{nap}(v_1) \wedge \text{Subj}(v_1) = x_1)$

$H : \exists x_2 v_2 (\text{dog}(x_2) \wedge \text{white}(x_2) \wedge \text{black}(x_2) \wedge \text{sleep}(v_2) \wedge \text{Subj}(v_2) = x_2)$

step 0

p_1: $\text{dog}(x_1)$
p_2: $\text{white}(x_1)$
p_3: $\text{black}(x_1)$
p_4: $\text{Subj}(v_1) = x_1$
p_5: $\text{nap}(v_1)$

g_1: $\text{dog}(x_2)$
g_2: $\text{white}(x_2)$
g_3: $\text{black}(x_2)$
g_4: $\text{Subj}(v_2) = x_2$
g_5: $\text{sleep}(v_2)$

- Decompose T and H into:
  - Pool of logical premises P.
  - List of sub-goals G.

Proving strategy and Axiom construction

$T: \exists x_1 v_1 (\text{dog}(x_1) \wedge \text{white}(x_1) \wedge \text{black}(x_1) \wedge \text{nap}(v_1) \wedge \text{Subj}(v_1) = x_1)$

$H: \exists x_2 v_2 (\text{dog}(x_2) \wedge \text{white}(x_2) \wedge \text{black}(x_2) \wedge \text{sleep}(v_2) \wedge \text{Subj}(v_2) = x_2)$

step 1

p_1: dog(x_1)
p_2: white(x_1)
p_3: black(x_1)
p_4: Subj$(v_1) = x_1$
p_5: nap(v_1)

~~g_1: dog(x_1)~~
~~g_2: white(x_1)~~
~~g_3: black(x_1)~~
g_4: Subj$(v_2) = x_1$
g_5: sleep(v_2)

- Decompose T and H into:
  - Pool of logical premises P.
  - List of sub-goals G.
- Variable unification $x_2 := x_1$.
  - Prove g_1, g_2 and g_3 ...
  - ... using p_1, p_2 and p_3.

Proving strategy and Axiom construction

$T : \exists x_1 v_1 (\mathsf{dog}(x_1) \wedge \mathsf{white}(x_1) \wedge \mathsf{black}(x_1) \wedge \mathsf{nap}(v_1) \wedge \mathsf{Subj}(v_1) = x_1)$

$H : \exists x_2 v_2 (\mathsf{dog}(x_2) \wedge \mathsf{white}(x_2) \wedge \mathsf{black}(x_2) \wedge \mathsf{sleep}(v_2) \wedge \mathsf{Subj}(v_2) = x_2)$

step 2

p_1: dog(x_1)
p_2: white(x_1)
p_3: black(x_1)
p_4: Subj$(v_1) = x_1$
p_5: nap(v_1)

~~g_1: dog(x_1)~~
~~g_2: white(x_1)~~
~~g_3: black(x_1)~~
~~g_4: Subj$(v_1) = x_1$~~
g_5: sleep(v_1)

- Decompose T and H into:
  - Pool of logical premises P.
  - List of sub-goals G.
- Variable unification $x_2 := x_1$.
  - Prove g_1, g_2 and g_3 ...
  - ... using p_1, p_2 and p_3.
- Variable unification $v_2 := v_1$.
  - Prove g_4 using p_4.

Proving strategy and Axiom construction

$T : \exists x_1 v_1 (\text{dog}(x_1) \wedge \text{white}(x_1) \wedge \text{black}(x_1) \wedge \text{nap}(v_1) \wedge \text{Subj}(v_1) = x_1)$
$H : \exists x_2 v_2 (\text{dog}(x_2) \wedge \text{white}(x_2) \wedge \text{black}(x_2) \wedge \text{sleep}(v_2) \wedge \text{Subj}(v_2) = x_2)$

step 3

p_1: dog(x_1)
p_2: white(x_1)
p_3: black(x_1)
p_4: Subj$(v_1) = x_1$
p_5: nap(v_1)

~~g_1: dog(x_1)~~
~~g_2: white(x_1)~~
~~g_3: black(x_1)~~
~~g_4: Subj$(v_1) = x_1$~~
~~g_5: sleep(v_1)~~

- Decompose T and H into:
  - Pool of logical premises P.
  - List of sub-goals G.
- Variable unification $x_2 := x_1$.
  - Prove g_1, g_2 and g_3 ...
  - ... using p_1, p_2 and p_3.
- Variable unification $v_2 := v_1$.
  - Prove g_4 using p_4.
- Inject axiom $\forall v.\text{nap}(v) \rightarrow \text{sleep}(v)$.
  - nap(v_1) and sleep(v_1) share variable.
  - nap-sleep $\in$ WordNet.
  - Continue proof.

Proving strategy and Axiom construction

$T: \exists x_1 v_1 (\text{dog}(x_1) \wedge \text{white}(x_1) \wedge \text{black}(x_1) \wedge \text{nap}(v_1) \wedge \text{Subj}(v_1) = x_1)$

$H: \exists x_2 v_2 (\text{dog}(x_2) \wedge \text{white}(x_2) \wedge \text{black}(x_2) \wedge \text{sleep}(v_2) \wedge \text{Subj}(v_2) = x_2)$

step 3

p_1: dog(x_1)
p_2: white(x_1)
p_3: black(x_1)
p_4: Subj$(v_1) = x_1$
p_5: nap(v_1)

~~g_1: dog(x_1)~~
~~g_2: white(x_1)~~
~~g_3: black(x_1)~~
~~g_4: Subj$(v_1) = x_1$~~
~~g_5: sleep(v_1)~~

- Decompose T and H into:
  - Pool of logical premises P.
  - List of sub-goals G.
- Variable unification $x_2 := x_1$.
  - Prove g_1, g_2 and g_3 ...
  - ... using p_1, p_2 and p_3.
- Variable unification $v_2 := v_1$.
  - Prove g_4 using p_4.
- Inject axiom $\forall v.\text{nap}(v) \to \text{sleep}(v)$.
  - nap(v_1) and sleep(v_1) share variable.
  - nap-sleep $\in$ WordNet.
  - Continue proof.

Proving strategy and Axiom construction

$T : \exists x_1 v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge nap(v_1) \wedge Subj(v_1) = x_1)$

$H : \exists x_1 v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge sleep(v_1) \wedge Subj(v_1) = x_1)$

Proving strategy and Axiom construction

$T : \exists x_1 \, v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge nap(v_1) \wedge Subj(v_1) = x_1)$

$H : \exists x_1 \, v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge sleep(v_1) \wedge Subj(v_1) = x_1)$

- Variable unification from proof...

Proving strategy and Axiom construction

$T : \exists x_1 v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge nap(v_1) \wedge Subj(v_1) = x_1)$

$H : \exists x_1 v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge sleep(v_1) \wedge Subj(v_1) = x_1)$

- Variable unification from proof...
  - Defines an alignment between logic predicates.
  - Most theorem provers perform backtracking in the search of best alignment.

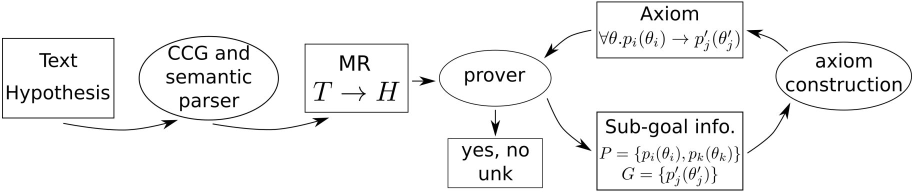
Proving strategy and Axiom construction

$T : \exists x_1 v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge nap(v_1) \wedge Subj(v_1) = x_1)$

$H : \exists x_1 v_1 (dog(x_1) \wedge white(x_1) \wedge black(x_1) \wedge sleep(v_1) \wedge Subj(v_1) = x_1)$

- Variable unification from proof...
  - Defines an alignment between logic predicates.
  - Most theorem provers perform backtracking in the search of best alignment.
- Better identify logic/textual relations:
  - $\forall v.\mathrm{nap}(v) \rightarrow \mathrm{sleep}(v)$.

System



1. Tokenize T and H.
2. Syntactic parsing with C&C and EasyCCG.
3. Obtain Meaning Representations with ccg2lambda.
4. Monitor proof and inject axioms on-demand:
   - synonymy (e.g. house $\rightarrow$ home),
   - hypernymy (e.g. sea $\rightarrow$ water),
   - adjectival similarity (e.g. huge $\rightarrow$ big),
   - derivationally related forms (e.g. accommodating $\rightarrow$ accommodation),
   - inflection relations (e.g. wooded $\rightarrow$ wood),
   - antonymy relations (e.g. big $\rightarrow$ $\neg$small).

Evaluation

SICK dataset

- Size: $4,500/500/4,927$ for training, dev. and testing.
- Label distribution: $.29/.15/.56$ for yes/no/unk.
- About $212,000$ running words.
- Average premise and conclusion length: 10.6.
- No parameter estimation.

Evaluation

SICK dataset

- Size: $4,500/500/4,927$ for training, dev. and testing.
- Label distribution: $.29/.15/.56$ for yes/no/unk.
- About $212,000$ running words.
- Average premise and conclusion length: 10.6.
- No parameter estimation.

Examples:

Problem ID	T-H pairs	Entailment
1412	T: *Men are sawing logs .* H: *Men are cutting wood .*	Yes
4114	T: *There is no man eating food .* H: *A man is eating a pizza .*	No
718	T: *A few men in a competition are running outside .* H: *A few men are running competitions outside .*	Unknown

Evaluation

Results:

System	Prec.	Rec.	Acc.
Baseline (majority)	–	–	56.69

Evaluation

Results:

System	Prec.	Rec.	Acc.
Baseline (majority)	–	–	56.69
MLN	–	–	73.40
Nutcracker	–	–	74.30
Nutcracker-WN	–	–	77.50
Nutcracker-WN-PPDB	–	–	78.60
MLN-WN-PPDB	–	–	80.40
LangPro Hybrid-800	97.95	58.11	81.35
The Meaning Factory	93.63	60.64	81.60

Evaluation

Results:

System	Prec.	Rec.	Acc.
Baseline (majority)	–	–	56.69
MLN	–	–	73.40
Nutcracker	–	–	74.30
Nutcracker-WN	–	–	77.50
Nutcracker-WN-PPDB	–	–	78.60
MLN-WN-PPDB	–	–	80.40
LangPro Hybrid-800	97.95	58.11	81.35
The Meaning Factory	93.63	60.64	81.60
No axioms	98.90	46.48	76.65
Naïve	92.99	59.70	80.98
SPSA,WN,VO	97.04	63.64	**83.13**

Evaluation

Results:

System	Prec.	Rec.	Acc.
Baseline (majority)	–	–	56.69
MLN	–	–	73.40
Nutcracker	–	–	74.30
Nutcracker-WN	–	–	77.50
Nutcracker-WN-PPDB	–	–	78.60
MLN-WN-PPDB	–	–	80.40
LangPro Hybrid-800	97.95	58.11	81.35
The Meaning Factory	93.63	60.64	81.60
No axioms	98.90	46.48	76.65
Naïve	92.99	59.70	80.98
SPSA,WN,VO	97.04	63.64	**83.13**
SemantiKLUE	85.40	69.63	82.32
UNAL-NLP	81.99	76.80	83.05
ECNU	84.37	74.37	83.64
Illinois-LH	81.56	81.87	84.57
MLN-eclassif (CL2016)	–	–	85.10
Yin-Schutze (EACL2017)	–	–	**87.10**

Error analysis

(more complex examples in back-up slide)

Prob. ID	T-H pairs	Gold	System	Axioms needed
1412	T: *Men are sawing logs .* H: *Men are cutting wood .*	Yes	Yes	$\forall v.\mathrm{saw}(v) \rightarrow \mathrm{cut}(v)$ $\forall x.\mathrm{log}(x) \rightarrow \mathrm{wood}(x)$
2404	T: *The lady is slicing a tomato .* H: *There is no one cutting a tomato .*	No	No	$\forall v.\mathrm{slice}(v) \rightarrow \mathrm{cut}(v)$
2895	T: *The man isn't lifting weights .* H: *The man is lifting barbells .*	No	No	$\forall x.\mathrm{weight}(x) \rightarrow \mathrm{barbell}(x)$

Error analysis

(more complex examples in back-up slide)

Prob. ID	T-H pairs	Gold	System	Axioms needed
1412	T: *Men are sawing logs .* H: *Men are cutting wood .*	Yes	Yes	$\forall v.\mathsf{saw}(v) \rightarrow \mathsf{cut}(v)$ $\forall x.\mathsf{log}(x) \rightarrow \mathsf{wood}(x)$
2404	T: *The lady is slicing a tomato .* H: *There is no one cutting a tomato .*	No	No	$\forall v.\mathsf{slice}(v) \rightarrow \mathsf{cut}(v)$
2895	T: *The man isn't lifting weights .* H: *The man is lifting barbells .*	No	No	$\forall x.\mathsf{weight}(x) \rightarrow \mathsf{barbell}(x)$
530	T: *A biker is wearing gear which is black .* H: *A biker wearing black is breaking the gears .*	Unk	Yes	

Error analysis

(more complex examples in back-up slide)

Prob. ID	T-H pairs	Gold	System	Axioms needed
1412	T: *Men are sawing logs .* H: *Men are cutting wood .*	Yes	Yes	$\forall v.\mathrm{saw}(v) \rightarrow \mathrm{cut}(v)$ $\forall x.\mathrm{log}(x) \rightarrow \mathrm{wood}(x)$
2404	T: *The lady is slicing a tomato .* H: *There is no one cutting a tomato .*	No	No	$\forall v.\mathrm{slice}(v) \rightarrow \mathrm{cut}(v)$
2895	T: *The man isn't lifting weights .* H: *The man is lifting barbells .*	No	No	$\forall x.\mathrm{weight}(x) \rightarrow \mathrm{barbell}(x)$
530	T: *A biker is wearing gear which is black .* H: *A biker wearing black is breaking the gears .*	Unk	Yes	
1495	T: *A man is playing a guitar .* H: *A man is strumming a guitar .*	Yes	Unk	$\forall v.\mathrm{play}(v) \rightarrow \mathrm{strum}(v)$
1266	T: *A band is playing on a stage .* H: *A band is playing onstage .*	Yes	Unk	"on a stage" $\rightarrow$ "onstage"
2166	T: *A woman is sewing with a machine .* H: *A woman is using a machine made for sewing .*	Yes	Unk	"sewing with a machine" $\rightarrow$ "using a machine made for sewing"
384	T: *A white and tan dog is running through the tall and green grass .* H: *A white and tan dog is running through a field .*	Yes	Unk	"tall and green grass" $\rightarrow$ "field"

Phrasal Entailments with Visual Denotations

Phrasal Entailments with Visual Denotations

Recognizing phrase entailments is also necessary!

T: *men walk in the tall and green grass.*

$$\exists x.(\mathrm{man}(x) \rightarrow \exists y.(\mathrm{tall}(y) \wedge \mathrm{green}(y) \wedge \mathrm{grass}(y) \wedge \mathrm{walk}(x, y))$$

H: *men walk in the field.*

$$\exists x.(\mathrm{man}(x) \rightarrow \exists y.(\mathrm{field}(y) \wedge \mathrm{walk}(x, y))$$

Problem:

- Such knowledge can not be found in databases (e.g. WordNet, PPDB).
- Semantic relatedness $\neq$ semantic entailment.
- Distributional approaches (e.g. word2vec) are not effective:
  - piano $\not\Rightarrow$ guitar, cat $\not\Rightarrow$ dog

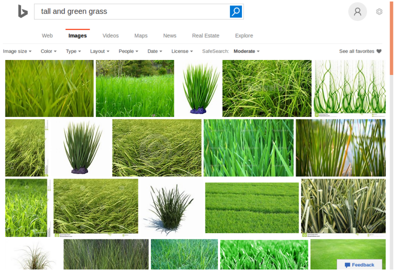
Phrasal Entailments with Visual Denotations

Get visual denotations of phrases and compare images.

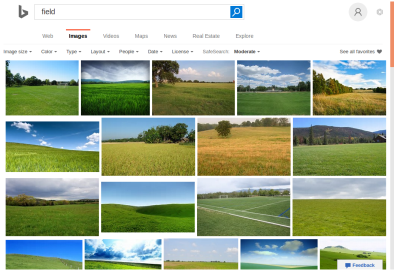
T: *men walk in the tall and green grass.*

H: *men walk in the field.*

tall and green grass



field



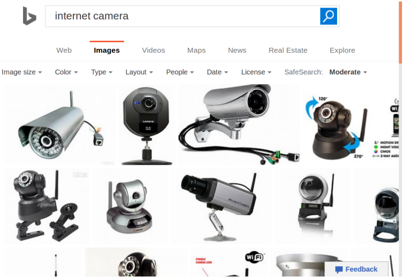
Phrasal Entailments with Visual Denotations

Get visual denotations of phrases and compare images.

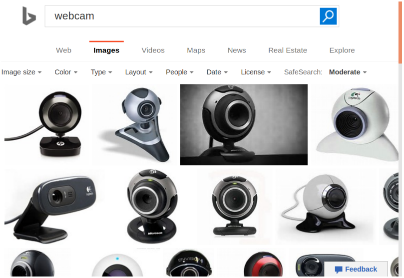
T: *He chats with his wife via internet camera.*

H: *He chats with his wife via webcam.*

internet camera

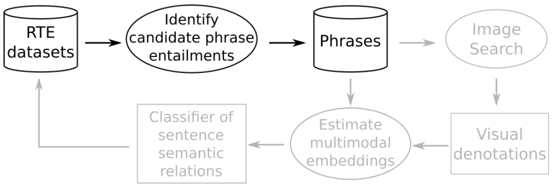


webcam

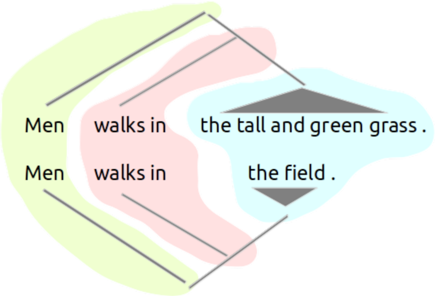


Phrasal Entailments with Visual Denotations

Step 1: phrase pair identification

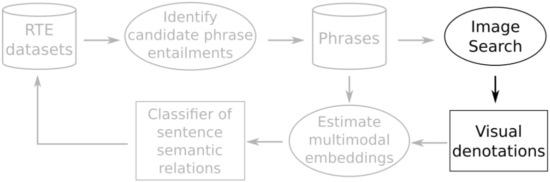


- Identify examples of phrase equivalences.

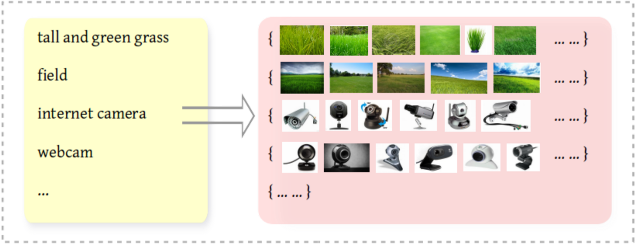


Phrasal Entailments with Visual Denotations

Step 2: obtain visual denotations

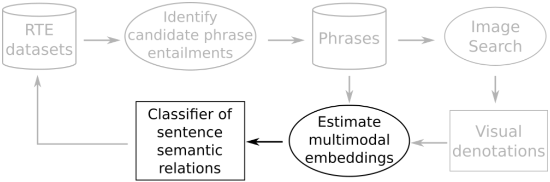


- Query images using phrases.

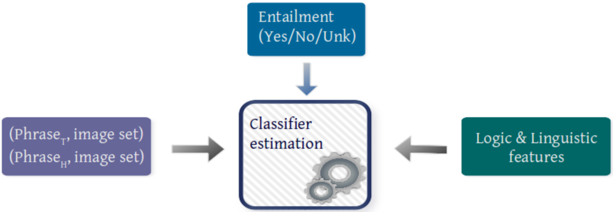


Phrasal Entailments with Visual Denotations

Step 3: Learn RTE Classifier

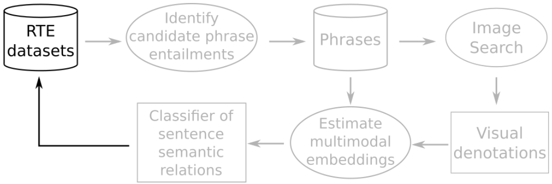


- Learn parameters of RTE classifier.

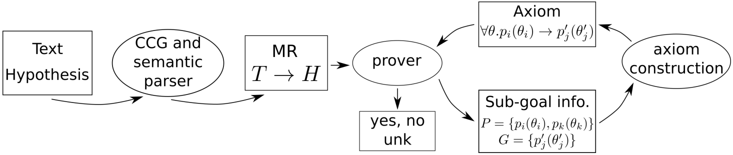


Phrasal Entailments with Visual Denotations

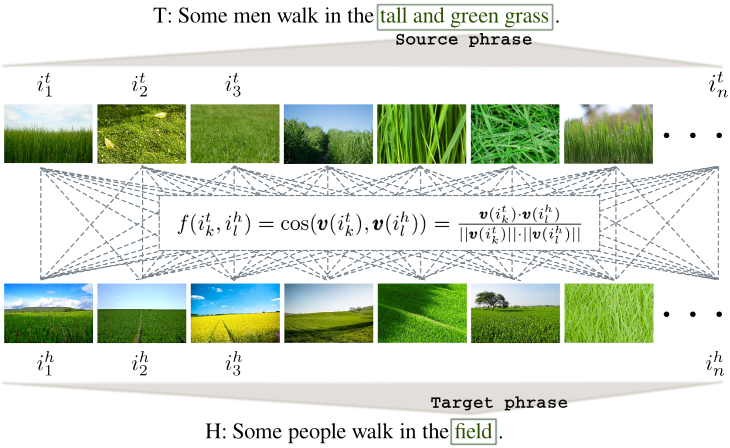
Step 4: Integrate into RTE pipeline



- Integrate on RTE pipeline and evaluate.



Phrasal Entailments with Visual Denotations



- Select best and worst phrase pair according to:

$$\text{score}(t, h) = \frac{1}{|I_h|} \sum_{i_l^h \in I_h} \max_{i_k^t \in I_t} f(i_k^t, i_l^h)$$

Phrasal Entailments with Visual Denotations

Results when using visual denotations

System	Prec.	Rec.	Acc.
`ccg2lambda` + images	90.24	71.08	**84.29**
`ccg2lambda`, only text	96.95	62.65	83.13
L&H, text + images	–	–	82.70
L&H, only text	–	–	81.50
Baseline (majority)	–	–	56.69

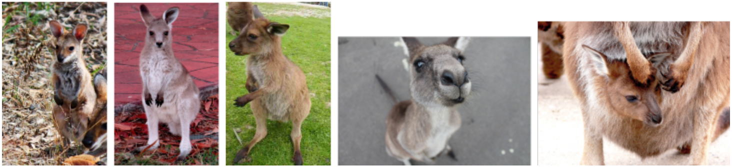
Phrasal Entailments with Visual Denotations

Examples

True positive:

T: The woman is picking up a kangaroo that is little.

H: The woman is picking up a baby kangaroo.



Phrasal Entailments with Visual Denotations

Examples

False positive:

T: A monkey is wading through a marsh.

H: A monkey is wading through a river.

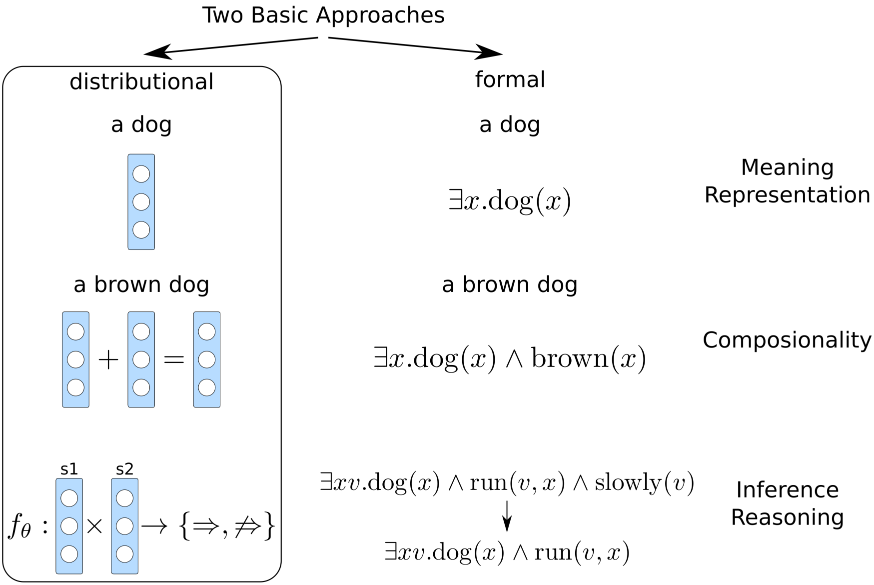
Phrasal Entailments with Visual Denotations

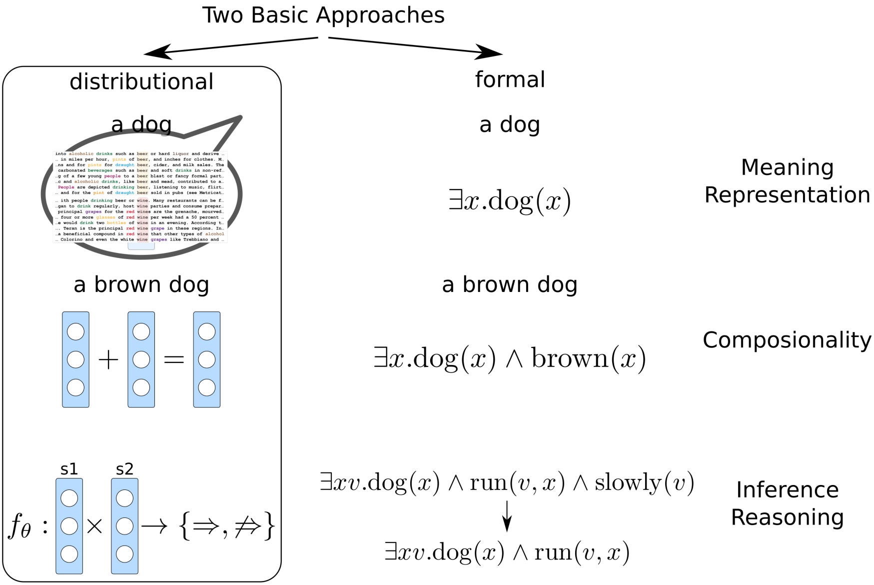
Examples

False negative:

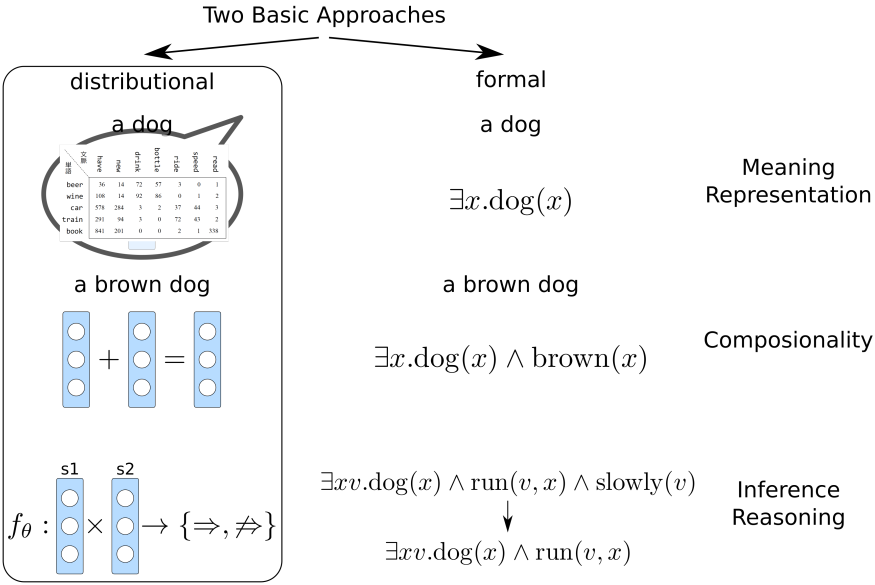
T: A boy is spanking a man with a $\boxed{\text{plastic sword}}$.

H: A boy is spanking a man with a $\boxed{\text{toy weapon}}$.

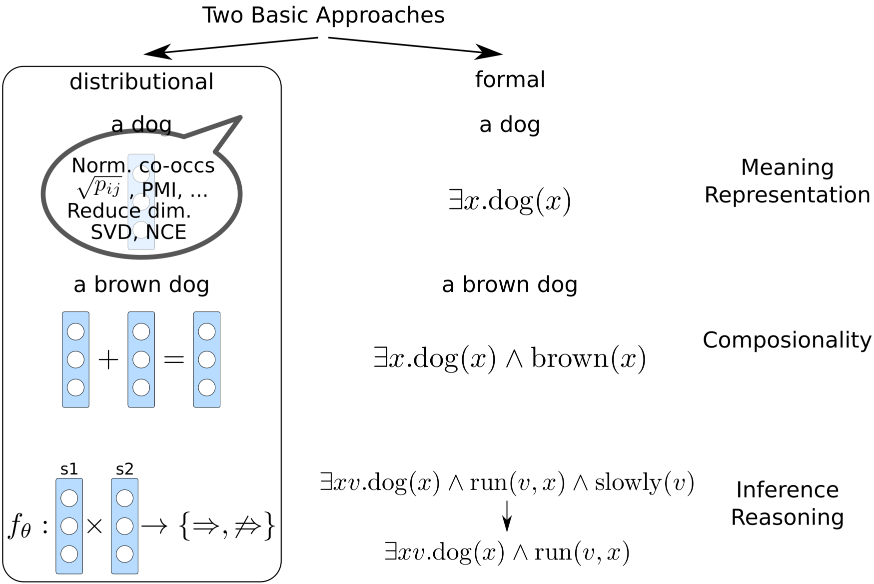

Two Basic Approaches
distributional
formal
a dog
a dog
$\exists x.\mathrm{dog}(x)$
Meaning Representation
a brown dog
a brown dog
+
=
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
s1
s2
$f_\theta :$
×
$\rightarrow \{\Rightarrow, \not\Rightarrow\}$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x)$
Inference Reasoning

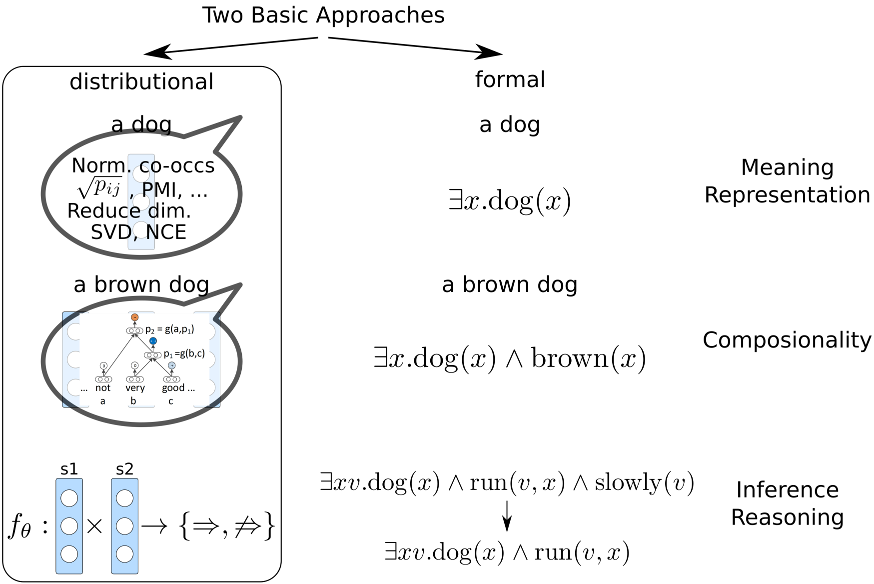


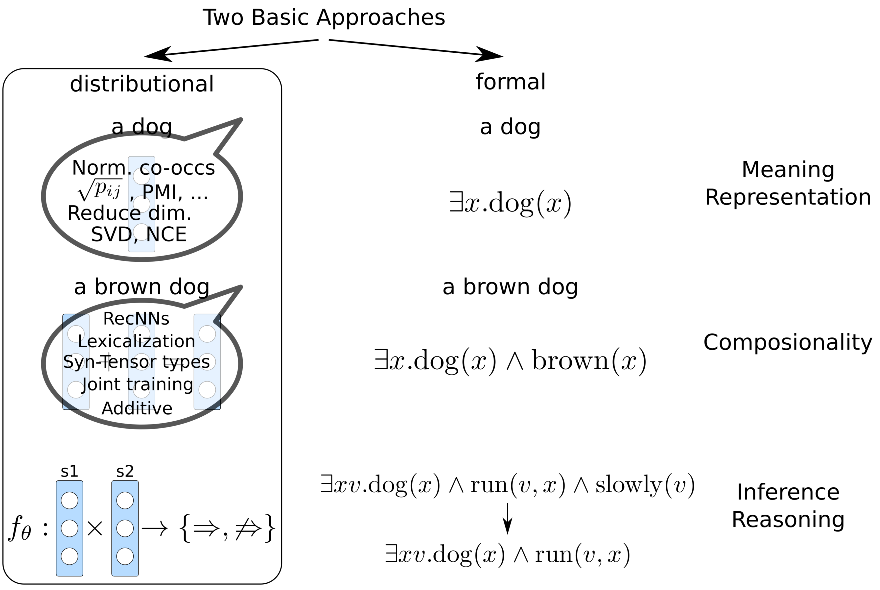
Two Basic Approaches
distributional
formal
a dog
a dog
$\exists x.\mathrm{dog}(x)$
Meaning Representation
a brown dog
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
s1
s2
$f_\theta : \cdot \times \cdot \rightarrow \{\Rightarrow, \not\Rightarrow\}$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x)$
Inference Reasoning



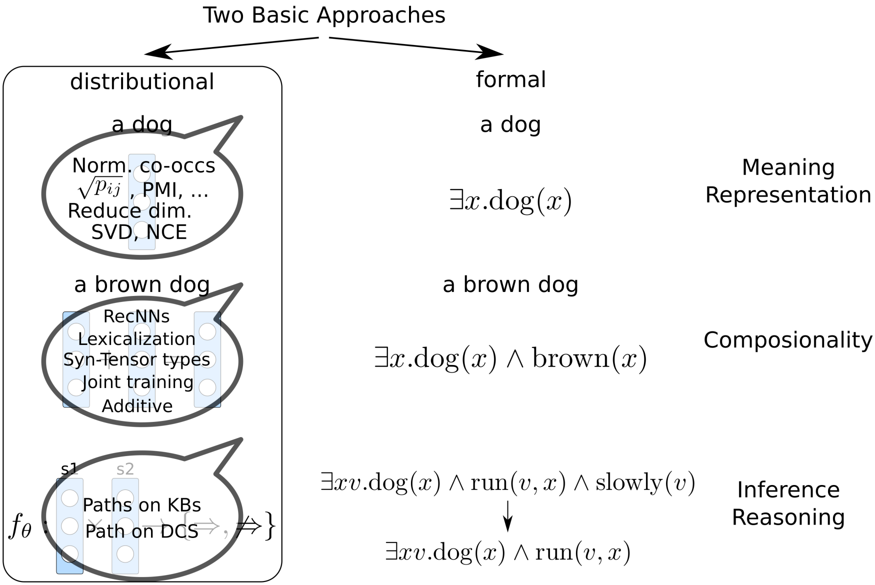
Two Basic Approaches
distributional
formal
a dog
have new drink bottle ride speed read
beer 36 14 72 57 3 0 1
wine 108 14 92 86 0 1 2
car 578 284 3 2 37 44 3
train 291 94 3 0 72 43 2
book 841 201 0 0 2 1 338
a brown dog
s1
s2
$f_\theta : \times \rightarrow \{\Rightarrow, \not\Rightarrow\}$
a dog
$\exists x.\mathrm{dog}(x)$
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x)$
Meaning Representation
Composionality
Inference Reasoning


Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a dog
$\exists x.\mathrm{dog}(x)$
Meaning Representation
a brown dog
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
s1
s2
$f_\theta : \cdot \times \cdot \rightarrow \{\Rightarrow, \not\Rightarrow\}$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x)$
Inference Reasoning

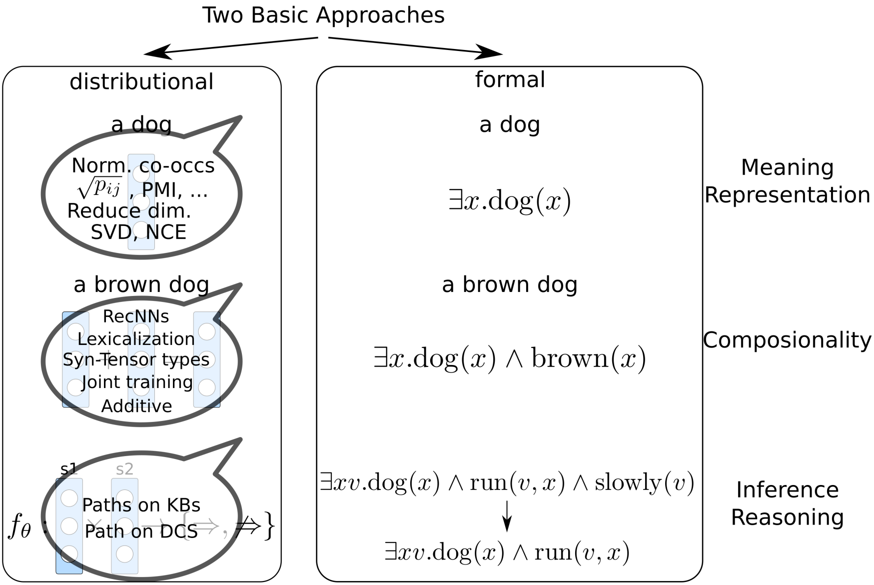

Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a brown dog
$p_2 = g(a,p_1)$
$p_1 = g(b,c)$
... not very good ...
a b c
s1
s2
$f_\theta : \times \rightarrow \{\Rightarrow, \not\Rightarrow\}$
a dog
$\exists x.\mathrm{dog}(x)$
Meaning Representation
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x)$
Inference Reasoning



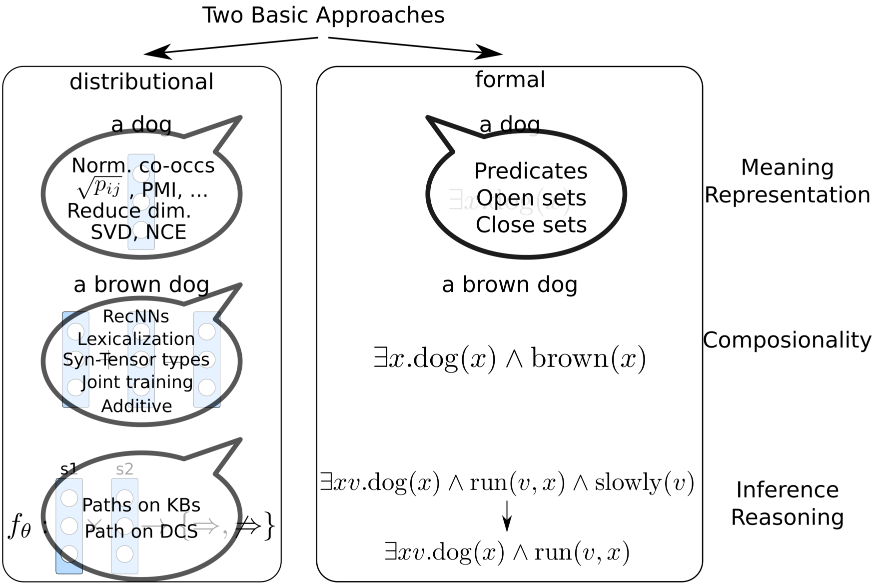
Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
s1
s2
$f_\theta : \times \rightarrow \{\Rightarrow, \not\Rightarrow\}$
a dog
$\exists x.\mathrm{dog}(x)$
Meaning
Representation
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x)$
Inference
Reasoning



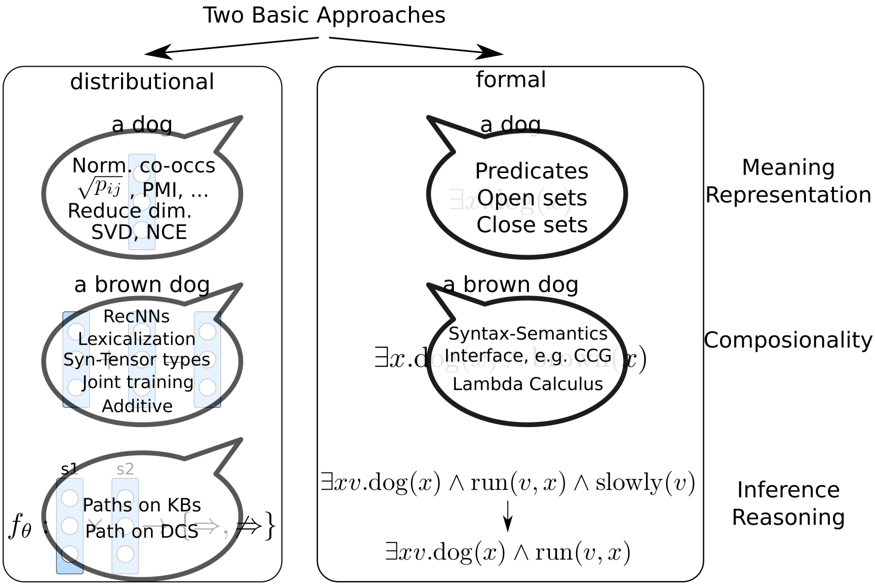
Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a dog
$\exists x.\mathrm{dog}(x)$
Meaning Representation
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
s1
s2
Paths on KBs
Path on DCS
$f_\theta : \times \longrightarrow \{\Rightarrow, \not\Rightarrow\}$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x)$
Inference Reasoning



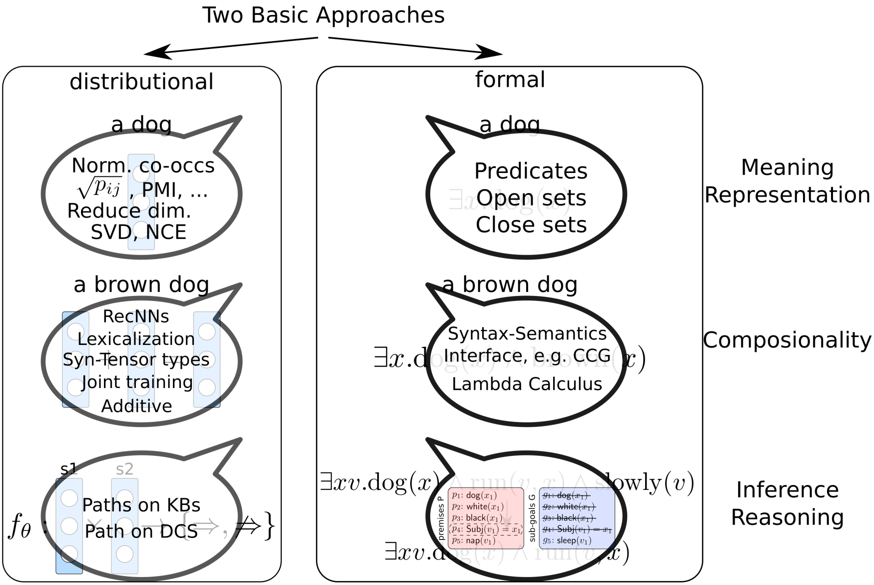
Two Basic Approaches
distributional
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
s1
s2
Paths on KBs
Path on DCS
$f_\theta : \times \longrightarrow \{\Rightarrow, \not\Rightarrow\}$
formal
a dog
$\exists x.\mathrm{dog}(x)$
a brown dog
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x)$
Meaning Representation
Composionality
Inference Reasoning

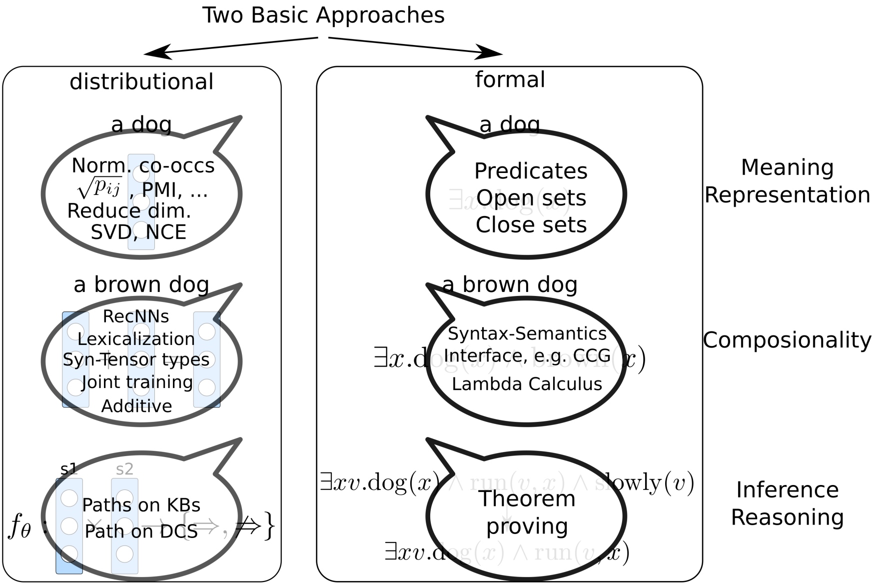


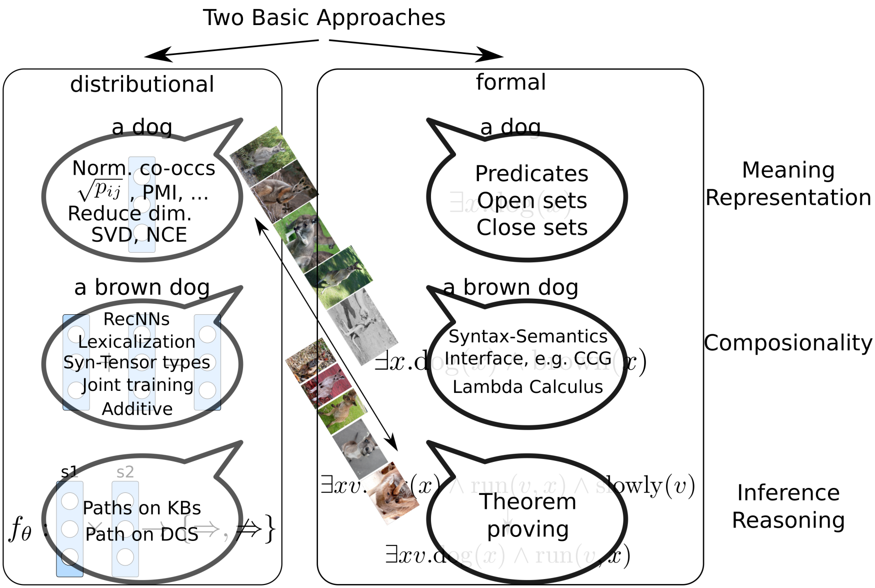
Two Basic Approaches
distributional
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
s1
s2
Paths on KBs
Path on DCS
$f_\theta : \times \to \{\Rightarrow, \not\Rightarrow\}$
formal
a dog
Predicates
Open sets
Close sets
$\exists x.\text{dog}(x)$
a brown dog
$\exists x.\text{dog}(x) \wedge \text{brown}(x)$
$\exists xv.\text{dog}(x) \wedge \text{run}(v, x) \wedge \text{slowly}(v)$
$\exists xv.\text{dog}(x) \wedge \text{run}(v, x)$
Meaning Representation
Composionality
Inference Reasoning



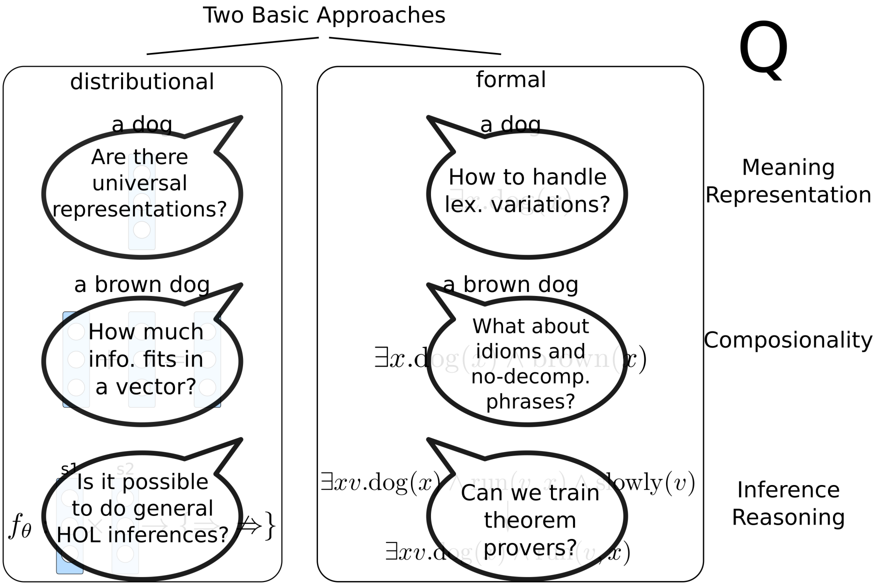
Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a dog
Predicates
Open sets
Close sets
Meaning
Representation
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
a brown dog
Syntax-Semantics
Interface, e.g. CCG
Lambda Calculus
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
Composionality
s1
s2
Paths on KBs
Path on DCS
$f_\theta : \times \to \{\Rightarrow, \not\Rightarrow\}$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x)$
Inference
Reasoning

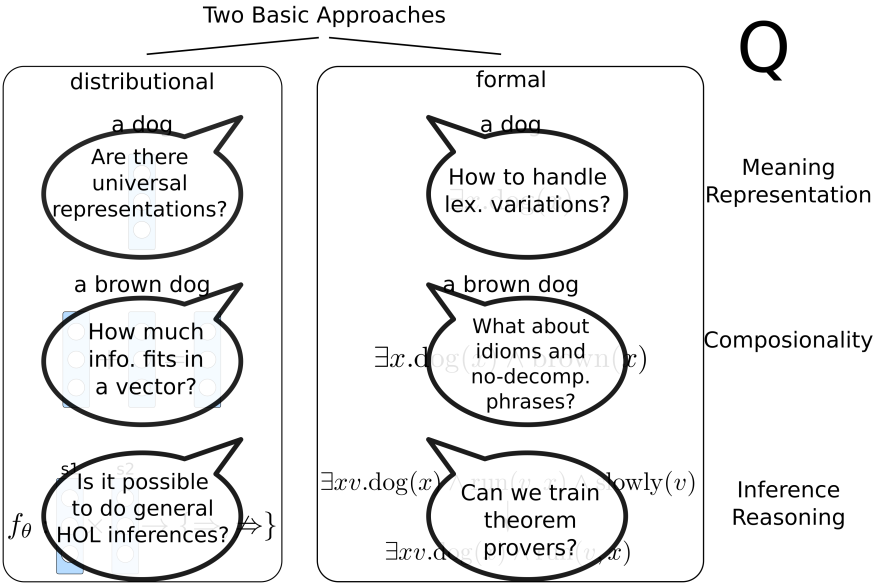

Two Basic Approaches
distributional
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
s1
s2
Paths on KBs
Path on DCS
formal
a dog
Predicates
Open sets
Close sets
a brown dog
Syntax-Semantics
Interface, e.g. CCG
Lambda Calculus
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v,x) \wedge \mathrm{slowly}(v)$
premises P
p_1: dog(x_1)
p_2: white(x_1)
p_3: black(x_1)
p_4: Subj(v_1) = x_1
p_5: nap(v_1)
sub-goals G
g_1: dog(x_1)
g_2: white(x_1)
g_3: black(x_1)
g_4: Subj(v_1) = x_1
g_5: sleep(v_1)
Meaning Representation
Composionality
Inference Reasoning


Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a dog
Predicates
Open sets
Close sets
Meaning
Representation
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
a brown dog
Syntax-Semantics
Interface, e.g. CCG
Lambda Calculus
Composionality
s1
s2
Paths on KBs
Path on DCS
Theorem
proving
Inference
Reasoning



Two Basic Approaches
distributional
formal
a dog
Norm. co-occs
$\sqrt{p_{ij}}$, PMI, ...
Reduce dim.
SVD, NCE
a brown dog
RecNNs
Lexicalization
Syn-Tensor types
Joint training
Additive
s1
s2
Paths on KBs
Path on DCS
$f_\theta :$
$\{\Rightarrow, \not\Rightarrow\}$
a dog
Predicates
Open sets
Close sets
$\exists x.\mathrm{dog}(x)$
a brown dog
Syntax-Semantics
Interface, e.g. CCG
Lambda Calculus
$\exists x.\mathrm{dog}(x) \wedge \mathrm{brown}(x)$
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x) \wedge \mathrm{slowly}(v)$
Theorem
proving
$\exists xv.\mathrm{dog}(x) \wedge \mathrm{run}(v, x)$
Meaning
Representation
Composionality
Inference
Reasoning


Two Basic Approaches
Q
distributional
formal
a dog
Are there universal representations?
a dog
How to handle lex. variations?
Meaning Representation
a brown dog
How much info. fits in a vector?
a brown dog
What about idioms and no-decomp. phrases?
Composionality
Is it possible to do general HOL inferences?
Can we train theorem provers?
Inference Reasoning



Thank you! Ran Tian, Koji Mineshima, Pascual Martínez-Gómez.

Reference I

Ajdukiewicz, K. (1935) “Die syntaktische Konnexit/”at”, *Studia Philosophica* **1**, pp.1–27.

Bar-Hillel, Y. (1953) “A quasi-arithmetical notation for syntactic description”, *Language* **29**(1), pp.47–58.

Barwise, J. and R. Cooper. (1981) “Generalized quantifiers and natural language”, *Linguistics and Philosophy* **4**(2), pp.159–219.

Bowman, S. R., G. Angeli, C. Potts, and C. D. Manning. (2015) “A large annotated corpus for learning natural language inference”, In the Proceedings of *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics.

Cooper, R., R. Crouch, J. van Eijck, C. Fox, J. van Genabith, J. Jaspers, H. Kamp, M. Pinkal, M. Poesio, S. Pulman, et al. (1994) “FraCaS — A Framework for Computational Semantics”, *Deliverable* **D16**.

Hobbs, J. R. (1985) “Ontological promiscuity”, In the Proceedings of *Proceedings of the 23rd annual meeting on Association for Computational Linguistics*. pp.60–69.

Reference II

Kamp, H. and U. Reyle. (1993) “From discourse to logic: An introduction to modeltheoretic semantics of natural language, formal logic and DRT”.

Marelli, M., S. Menini, M. Baroni, L. Bentivogli, R. Bernardi, and R. Zamparelli. (2014) “A SICK cure for the evaluation of compositional distributional semantic models.”, In the Proceedings of *Proceedings of LREC2014*. pp.216–223.

Parsons, T. (1990) *Events in the Semantics of English*. MIT Press.

Steedman, M. (2000) *The Syntactic Process*. MIT Press.

Steedman, M. (2012) *Taking scope: The natural semantics of quantifiers*. Mit Press.