Compositionality or generalization?

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Franklin Medal Award Winner Barbara Partee

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“The use of the fictional unicorn created memorable examples of how a language like English could be broken down with logic to study its meaning.”

Central questions

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Where the questions lead me

- *Learning* semantic representations can lead to richer theories of language and language use,
- but compositionality is too constraining in these situations.

Plan

1. The compositionality principle
2. The compositionality heuristic
3. Semantic parsing
4. Recursive deep learning models
5. Conclusions

Compositional semantics and statistical NLP

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There has been a recent intensification of interest in "semantics" in computational linguistics. I write the word in scare quotes because there are very different views of what computational semantics is. Broadly, it divides into the view that word meaning can be modeled in distributional terms and the view that meaning is to be viewed in terms of model theory of the kind employed in formal semantics deriving from the seminal work of Richard Montague (1974).

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Not anymore!

The compositionality principle

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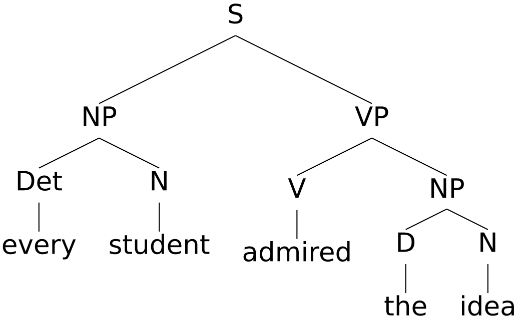

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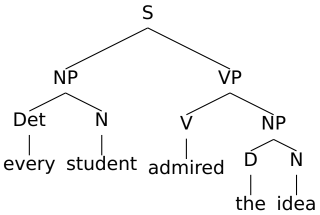

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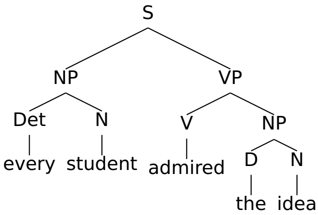

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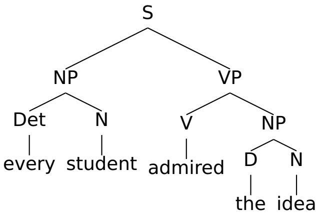

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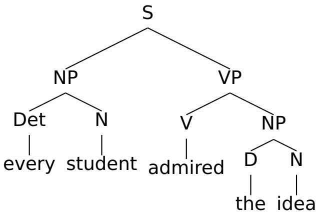

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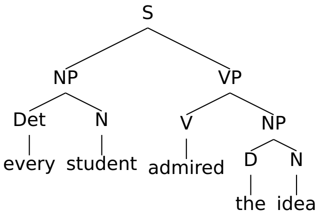

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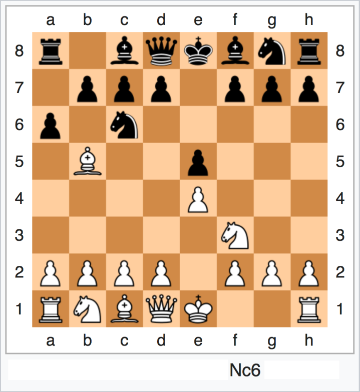

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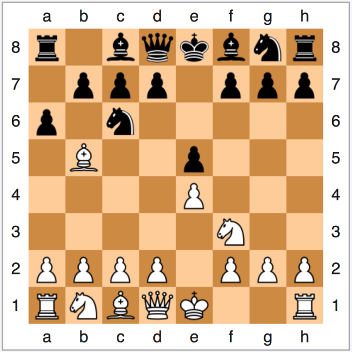

Position after 1.e4 e5 2.Nf3 Nc6 3.Bb5 a6

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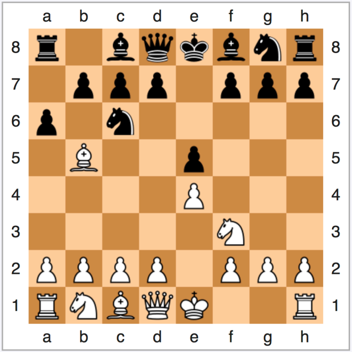

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Szabó (2012):

The second moral is that – given certain assumptions about meaning in chess notation – we can have productive and systematic understanding of representations even if the system itself is not compositional.

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Montague: Unconstrained compositionality

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The central idea is that anything that should count as a grammar should be able to be cast in the following form: the syntax is an algebra, the semantics is an algebra, and there is a homomorphism mapping elements of the syntactic algebra onto elements of the semantic algebra.

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[. . .]

It is the homomorphism requirement, which is in effect the compositionality requirement, that provides the most important constraint on UG in Montague's sense [. . .].

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Propositional logic semantics as homomorphism

$$
\begin{aligned}
[\![p]\!] &\in \{\emptyset, \{\emptyset\}\} \text{ for all propositional letters } p \\
[\![\neg\varphi]\!] &= \{\emptyset, \{\emptyset\}\} - [\![\varphi]\!] \\
[\![\varphi \vee \psi]\!] &= [\![\varphi]\!] \cup [\![\psi]\!] \\
[\![\varphi \wedge \psi]\!] &= [\![\varphi]\!] \cap [\![\psi]\!]
\end{aligned}
$$

Formal results

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Kazmi & Pelletier (1998) respond “Wait, what?”

Here is a non-compositional semantics:

- $[\![A]\!] = [\![B]\!]$
- $[\![C.A]\!] \neq [\![C.B]\!]$

Zadrozny showed how to create a kind of syntactic layer where compositionality holds. A similar argument is made by Dever 1999.

Dowty's context-free compositionality

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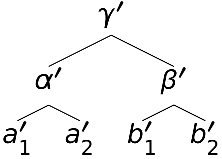
Dowty (2007):

When a rule f combines $\alpha, \beta(\ldots)$ to form γ, the corresponding semantic rule g that produces the meaning γ' of γ, from α' and β', may depend only on α' "as a whole", it may not depend on any meanings from which α' was formed compositionally by earlier derivational steps (similarly for β).



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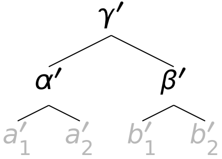

The compositionality heuristic

Compositionality as methodology

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Janssen (1997:461)

Compositionality is not a formal restriction on what can be achieved, but a methodology on how to proceed.

Example: Subjectless predicational adjuncts

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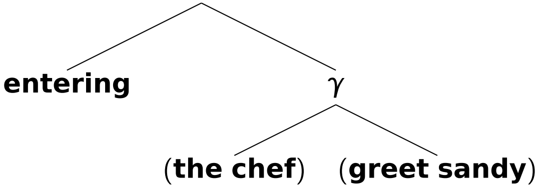
2. 

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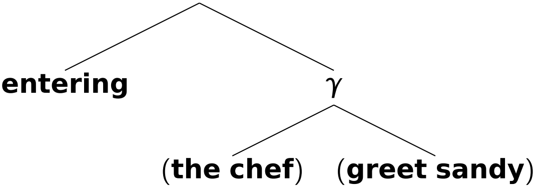
2. 

Potential rule

The implicit argument of a front subjectless predicational adjuncts must be the subject of the matrix clause.

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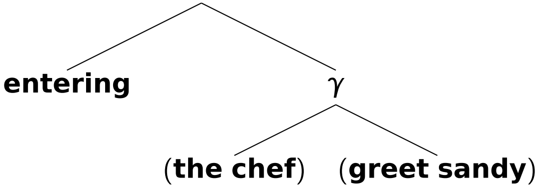
2. 

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Assuming context-free compositionality, the rule cannot be correct as stated.

Example: Subjectless predicational adjuncts

From `http://arnoldzwicky.wordpress.com/category/danglers/`:

1. “Having been in Australia for 17 years, a foreign national wishing to work in Australia must be of good character.”
2. “Fearing a massive lay-off, there was a general sense of relief when the boss announced there would be no new budget cuts.”
3. “Rich and creamy, your guests will never guess that this pie is light.”

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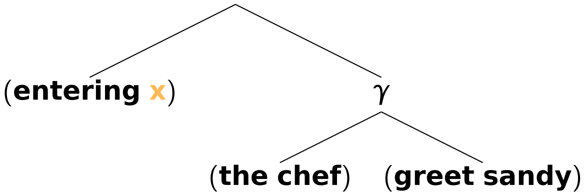
2. 

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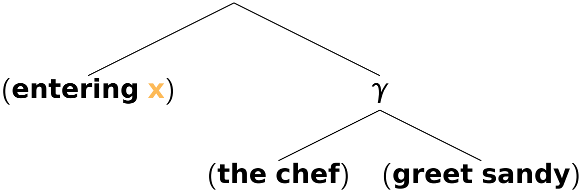
2. 

Subjects/topic correlation

In English, subjects are often topics.

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1. Exceptives adjoin only to universal quantifiers:
   a. Every Muppet except Kermit danced.
   b. No Muppet except Kermit danced.
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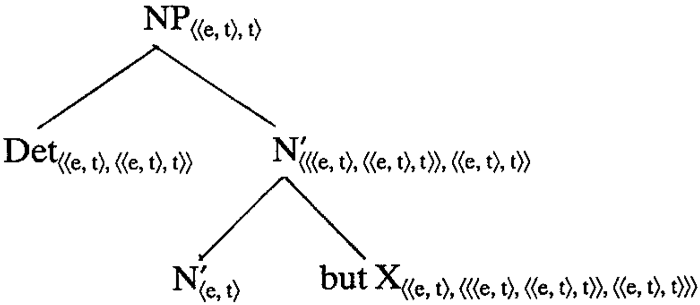
2. The exceptive's determiner affects VP entailments:
   a. Every Muppet except Kermit danced.
      ⇒ Kermit didn't dance.
   b. No Muppet except Kermit danced.
      ⇒ Kermit did dance.

Example: Exceptives

von Fintel (1993):



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   b. She didn't eat almost anything except pills. (Horn 2005)
   c. "an embarrassment for most Americans except his base."

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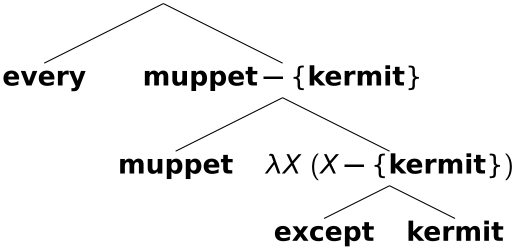
   b. She didn't eat almost anything except pills. (Horn 2005)
   c. "an embarrassment for most Americans except his base."
2. The VP entailments are merely implicated!
   a. Well, we can't find Karl, but we've verified that everyone except Karl has an alibi, so let's find out whether he does too. (Hoeksema 1996)
   b. "All of you are moving on [to Spanish 102] except for Jeff. Turns out you – pause for dramatic effect – will be seeing me next semester. In Spanish 102. Because he passed, you know, and I'm the only Spanish teacher." (*Community* 1:12).

Example: Exceptives



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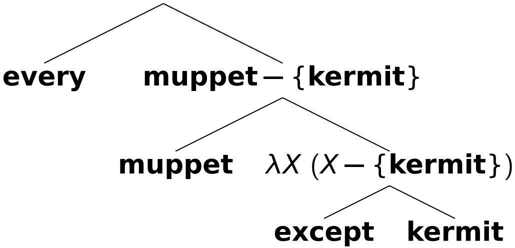

See also Higginbotham 1986 and
Nadathur & Lassiter (2014) on *unless*

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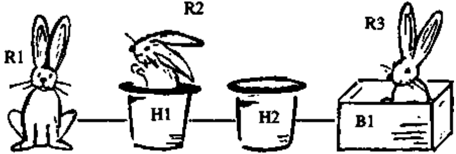

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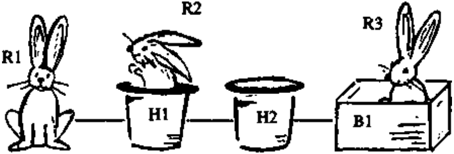

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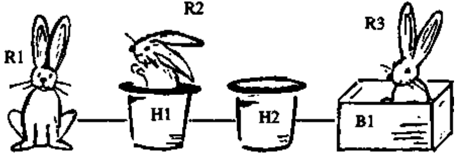

"Any compositional accounts of NP semantics [. . .] would judge (1) to be infelicitous."

Bumford (2017): these cases show us that definites introduce new discourse referents and constrain them, and these operations can take scope separately.

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Levin et al.’s (2018) novel compounds experiment:

Modifier	Head	Example	Top inference	Rate
Artifact	Artifact	stew skillet	Event	97.3%
Natural kind	Artifact	stream wheel	Event	96.4%
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(Why is there consensus that compounds aren't compositional but no real concern about *flat tire/beer/note* or *throw a ball/party/fight* (though see Keenan 1974; Hirst 1987; Partee 1984)?)

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   a. I saw a crane.
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2. Contextual ambiguity resolution is no longer taken to challenge compositionality:
   a. I saw a crane.
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3. Pragmatic free variables are no longer taken to be a challenge to compositionality:
   a. Being a master of disguise, Bill would fool anyone.
   b. Wearing his new outfit, Bill would fool anyone.

Semantic parsing

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2. The compositionality heuristic
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The semanticist's ideal

Every student attended a lecture

$$\forall z\ ((\textbf{student}\ z) \rightarrow (\exists x\ (\textbf{lecture}\ x) \wedge (\textbf{attended}\ x\ z)))$$

$\lambda g\ \forall z\ ((\textbf{student}\ z) \rightarrow (g\ z))$ $\quad$ $\lambda Q\ (Q\ (\lambda y\ (\exists x\ (\textbf{lecture}\ x) \wedge (\textbf{attended}\ x\ y))$

$\lambda f\ \lambda g\ \forall z\ ((f\ z) \rightarrow (g\ z))$ $\quad$ $\textbf{student}$ $\quad$ $\textbf{attended}_S$ $\quad$ $\lambda g\ (\exists x\ (\textbf{lecture}\ x) \wedge (g\ x))$

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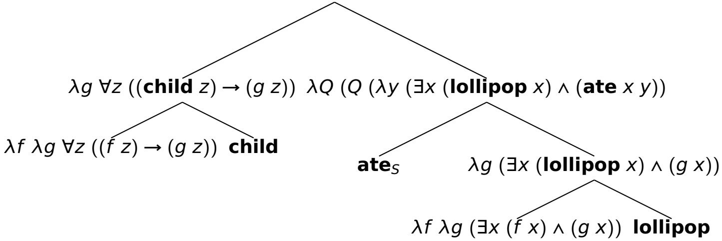
$$\forall z\ ((\mathbf{child}\ z) \rightarrow (\exists x\ (\mathbf{lollipop}\ x) \wedge (\mathbf{ate}\ x\ z)))$$



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$$\textbf{ate}_{l} \qquad \lambda g\ (\exists x\ (\textbf{lollipop}\ x) \wedge (g\ x))$$

$$\lambda f\ \lambda g\ (\exists x\ (f\ x) \wedge (g\ x)) \qquad \textbf{lollipop}$$

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$$\lambda f\ \lambda g\ (\exists x\ (f\ x) \wedge (g\ x)) \quad \mathbf{lollipop}$$

But is this really so ideal?

Crude grammars refined via learning

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Chat80 (Warren & Pereira 1982):

```
/* Sentences */
sentence(S) --> declarative(S), terminator(.) .
sentence(S) --> wh_question(S), terminator(?) .
sentence(S) --> yn_question(S), terminator(?) .
sentence(S) --> imperative(S), terminator(!) .

/* Noun Phrase */
np(np(Agmt,Pronoun,[]),Agmt,NPCase,def,_,Set,Nil) -->
  {is_pp(Set)},
  pers_pron(Pronoun,Agmt,Case),
  {empty(Nil), role(Case,decl,NPCase)}.

/* Prepositional Phrase */
pp(pp(Prep,Arg),Case,Set,Mask) -->
  prep(Prep),
  {prep_case(NPCase)},
  np(Arg,_,NPCase,_,Case,Set,Mask).
```

Crude grammars refined via learning

for $w \in \mathit{Words}$
    for $X \in \mathit{Categories}$
        for $d \in \mathit{Domain}$
            yield '$X \rightarrow w : d$'

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  for $X \in \mathit{Categories}$
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0	N	$\rightarrow$	*dog*	:	**dog**
0	V	$\rightarrow$	*dog*	:	$\mathbf{dog}_v$
0	N	$\rightarrow$	*dog*	:	**cat**
0	N	$\rightarrow$	*cat*	:	**cat**
0	N	$\rightarrow$	*cat*	:	**dog**
0	V	$\rightarrow$	*jump*	:	**dog**
0	V	$\rightarrow$	*jump*	:	**jump**

Crude grammars refined via learning

N
|
dog : **dog**

for $w \in \mathit{Words}$
  for $X \in \mathit{Categories}$
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1	N	→	*dog*	:	**dog**
0	V	→	*dog*	:	$\mathbf{dog}_V$
0	N	→	*dog*	:	**cat**
0	N	→	*cat*	:	**cat**
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0	N	→	*cat*	:	**cat**
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0	V	→	*jump*	:	**dog**
0	V	→	*jump*	:	**jump**

N
|
dog : **dog**

V
|
dog : $\mathbf{dog}_V$

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1	N	→	*dog*	:	**dog**
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1	N	→	*cat*	:	**cat**
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N
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V
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N
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Crude grammars refined via learning

for $w \in \mathit{Words}$
    for $X \in \mathit{Categories}$
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2	N	→	*dog*	:	**dog**
1	V	→	*dog*	:	$\mathbf{dog}_V$
0	N	→	*dog*	:	**cat**
1	N	→	*cat*	:	**cat**
0	N	→	*cat*	:	**dog**
0	V	→	*jump*	:	**dog**
0	V	→	*jump*	:	**jump**

N
|
dog : **dog**

V
|
dog : $\mathbf{dog}_V$

N
|
cat : **cat**

N
|
dog : **dog**

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```
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```

3	N	→	*dog*	:	**dog**
1	V	→	*dog*	:	$\mathbf{dog}_v$
0	N	→	*dog*	:	**cat**
1	N	→	*cat*	:	**cat**
0	N	→	*cat*	:	**dog**
0	V	→	*jump*	:	**dog**
0	V	→	*jump*	:	**jump**

N
dog : **dog**

N
dog : **dog**

V
dog : $\mathbf{dog}_v$

N
cat : **cat**

N
dog : **dog**

Crude grammars refined via learning

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    for $X \in \mathit{Categories}$
        for $d \in \mathit{Domain}$
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1	V	→	*dog*	:	$\mathbf{dog}_{v}$
0	N	→	*dog*	:	**cat**
1	N	→	*cat*	:	**cat**
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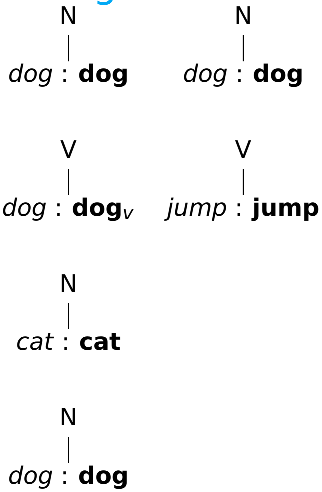
0	V	→	*jump*	:	**dog**
1	V	→	*jump*	:	**jump**



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N → *dog* : **dog**

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N
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N
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V
dog : $\mathbf{dog}_V$

V
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```
/* Sentences */
sentence(S) --> declarative(S), terminator(.) .
sentence(S) --> wh_question(S), terminator(?) .
sentence(S) --> yn_question(S), terminator(?) .
sentence(S) --> imperative(S), terminator(!) .

/* Noun Phrase */
np(np(Agmt,Pronoun,[]),Agmt,NPCase,def,_,Set,Nil) -->
  {is_pp(Set)},
  pers_pron(Pronoun,Agmt,Case),
  {empty(Nil), role(Case,decl,NPCase)}.

/* Prepositional Phrase */
pp(pp(Prep,Arg),Case,Set,Mask) -->
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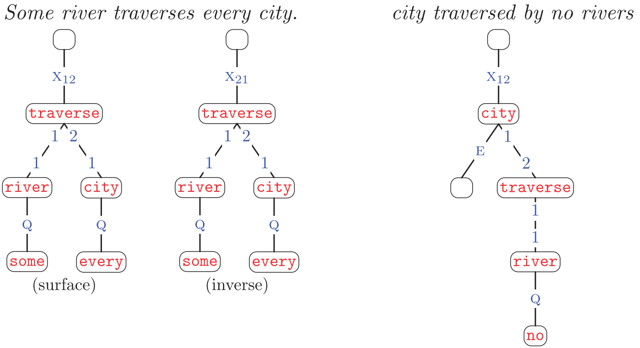
Crude grammars refined via learning

Liang et al. (2013):



(c) Quantifier scope ambiguity (Q, Q)

(d) Quantification (Q, E)

Additional feature functions

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2. Am I in the c-command domain of a negation?
3. Does this structure contain a specific set of tree fragments?
4. What is the average sentiment of words in this sentence?

Comparison with traditional semantic theory

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The linguist's ideal again

Every child ate a lollipop

$$\forall z\ ((\mathbf{child}\ z) \rightarrow (\exists x\ (\mathbf{lollipop}\ x) \wedge (\mathbf{ate}\ x\ z)))$$

$$\lambda g\ \forall z\ ((\mathbf{child}\ z) \rightarrow (g\ z)) \quad \lambda Q\ (Q\ (\lambda y\ (\exists x\ (\mathbf{lollipop}\ x) \wedge (\mathbf{ate}\ x\ y)))$$

$$\lambda f\ \lambda g\ \forall z\ ((f\ z) \rightarrow (g\ z)) \quad \mathbf{child}$$

$$\mathbf{ate}_S \quad \lambda g\ (\exists x\ (\mathbf{lollipop}\ x) \wedge (g\ x))$$

$$\lambda f\ \lambda g\ (\exists x\ (f\ x) \wedge (g\ x)) \quad \mathbf{lollipop}$$

Score: $+5$

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Every child ate a lollipop

$$\exists x\ (\mathbf{lollipop}\ x) \land (\forall z\ ((\mathbf{child}\ z) \rightarrow (\mathbf{ate}\ x\ z)))$$

- $\lambda g\ \forall z\ ((\mathbf{child}\ z) \rightarrow (g\ z))$
  - $\lambda f\ \lambda g\ \forall z\ ((f\ z) \rightarrow (g\ z))$
  - $\mathbf{child}$
- $\lambda Q\ (\exists x\ (\mathbf{lollipop}\ x) \land (Q\ (\lambda y\ (\mathbf{ate}\ x\ y))))$
  - $\mathbf{ate}_l$
  - $\lambda g\ (\exists x\ (\mathbf{lollipop}\ x) \land (g\ x))$
    - $\lambda f\ \lambda g\ (\exists x\ (f\ x) \land (g\ x))$
    - $\mathbf{lollipop}$

Score: -2

Recursive deep learning models

1. The compositionality principle
2. The compositionality heuristic
3. Semantic parsing
4. Recursive deep learning models
5. Conclusions

Composition with functions or with vectors

Composition with functions or with vectors

Functions

$$[\![A]\!] = \mathbf{fa}([\![B]\!], [\![C]\!])$$

$$[\![B]\!] \qquad [\![C]\!] = \mathbf{fa}([\![D]\!], [\![E]\!])$$

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Composition with functions or with vectors

Functions

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Vectors

Composition with functions or with vectors

Functions

$$\llbracket A \rrbracket = \mathbf{fa}(\llbracket B \rrbracket, \llbracket C \rrbracket)$$

$$\llbracket B \rrbracket \qquad \llbracket C \rrbracket = \mathbf{fa}(\llbracket D \rrbracket, \llbracket E \rrbracket)$$

$$\llbracket D \rrbracket \qquad \llbracket E \rrbracket$$

Vectors

$$f(\llbracket X \rrbracket^{DL}, \llbracket Y \rrbracket^{DL}) = \mathbf{g}\left(\left[\llbracket X \rrbracket^{DL}; \llbracket Y \rrbracket^{DL}\right] W\right)$$

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$$[\![B]\!]^{\mathrm{DL}} \qquad [\![C]\!]^{\mathrm{DL}} = \mathbf{g}\left(\left[[\![D]\!]^{\mathrm{DL}}; [\![E]\!]^{\mathrm{DL}}\right] W\right)$$

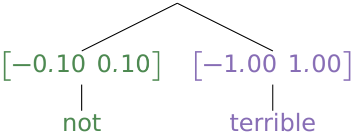
$$[\![D]\!]^{\mathrm{DL}} \qquad [\![E]\!]^{\mathrm{DL}}$$

Lexicon

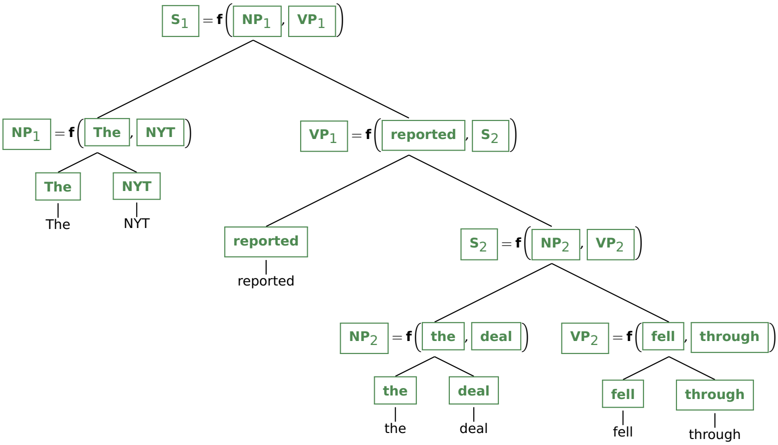
B	−0.42	0.10	0.12	...
D	−0.16	−0.21	0.29	...
E	−0.26	0.31	0.37	...

Simple example

$$\tanh\left(\begin{bmatrix}-0.10 & 0.10 & -1.00 & 1.00\end{bmatrix}\begin{bmatrix}0.06 & 0.32\\ -0.14 & -0.53\\ 1.24 & 0.00\\ 0.02 & 1.06\end{bmatrix}\right) = \begin{bmatrix}-0.85 & 0.75\end{bmatrix}$$



Recursive deep learning models



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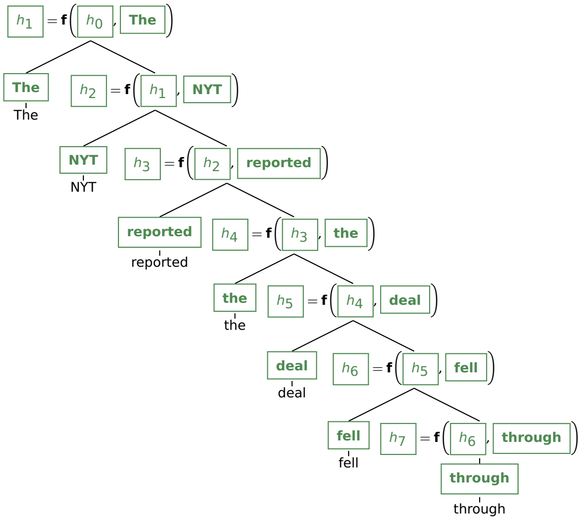

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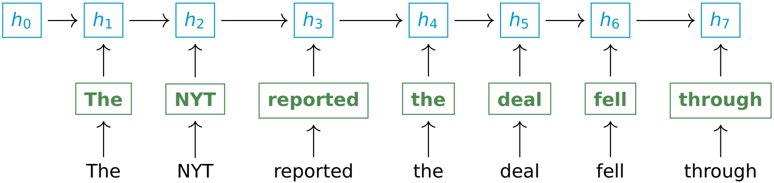
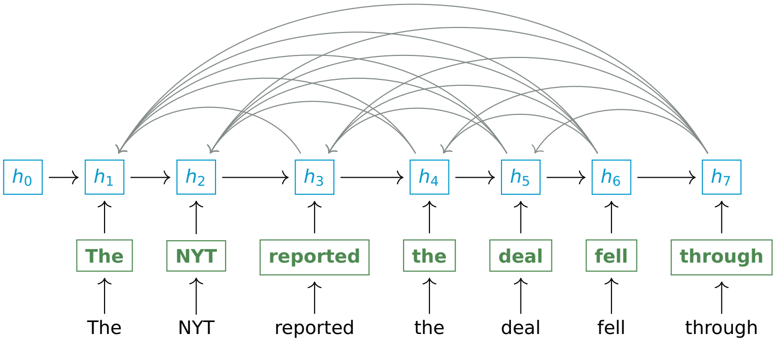


Recursive deep learning models

All our parses are wrong, but perhaps we can discover the right one(s).



A new perspective on compositionality

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Partee (1984):

Context-dependence, Ambiguity, and Challenges to Local, Deterministic Compositionality

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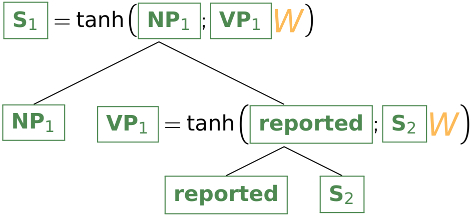
Global parameters creating local lexical effects



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$$\begin{bmatrix}-0.10 & 0.10\end{bmatrix} \quad \begin{bmatrix}-1.00 & 1.00\end{bmatrix}$$

not terrible

The linguist's ideal again

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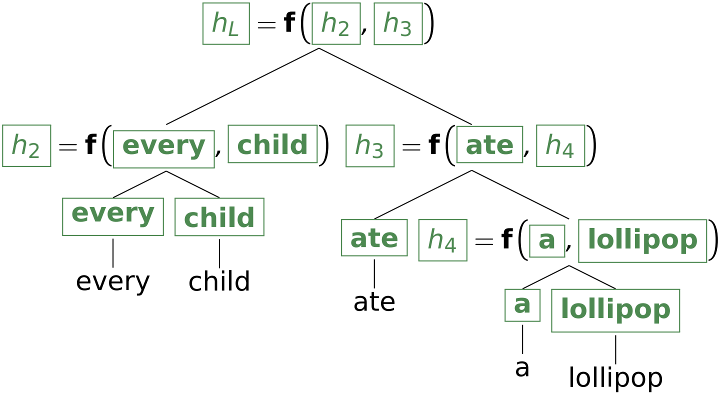

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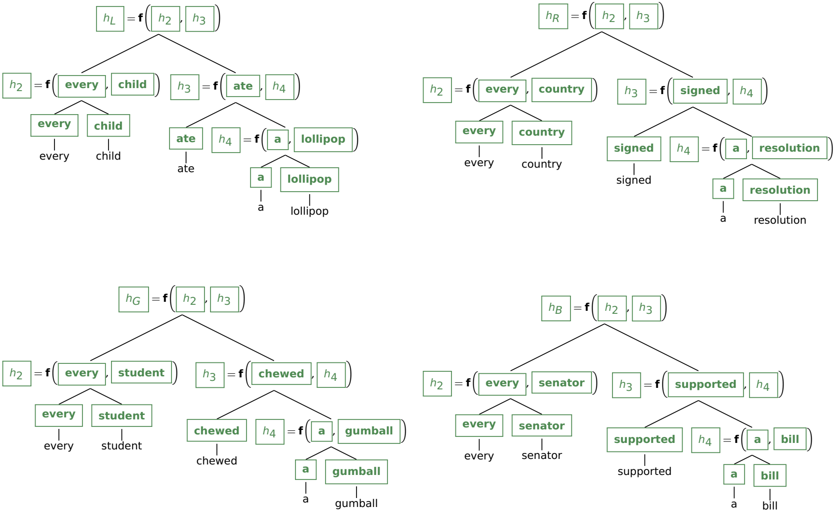

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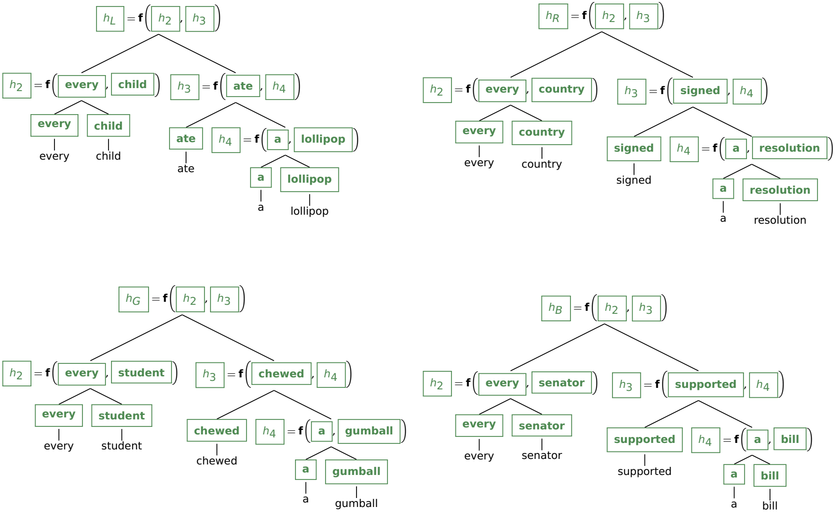
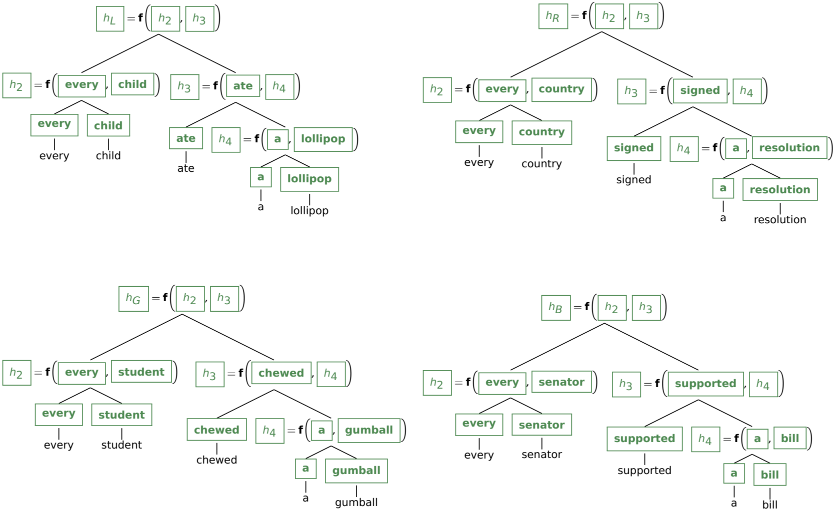
$$\mathbf{sim}\left(\boxed{h_L}, \boxed{h_G}\right) > \mathbf{sim}\left(\boxed{h_L}, \boxed{h_R}\right)$$

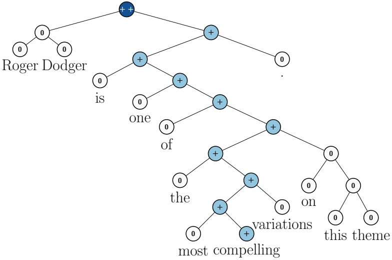


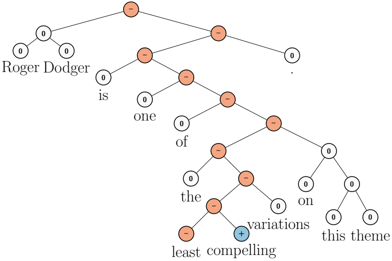
The linguist's ideal again

$$\mathbf{sim}\left(\boxed{h_L}, \boxed{h_G}\right) > \mathbf{sim}\left(\boxed{h_L}, \boxed{h_R}\right) \text{ or } \mathbf{g}\left(\boxed{h_L}, \boxed{\textbf{many lollipops eaten}}\right) = \textbf{entail}$$



Examples from Socher et al. 2013





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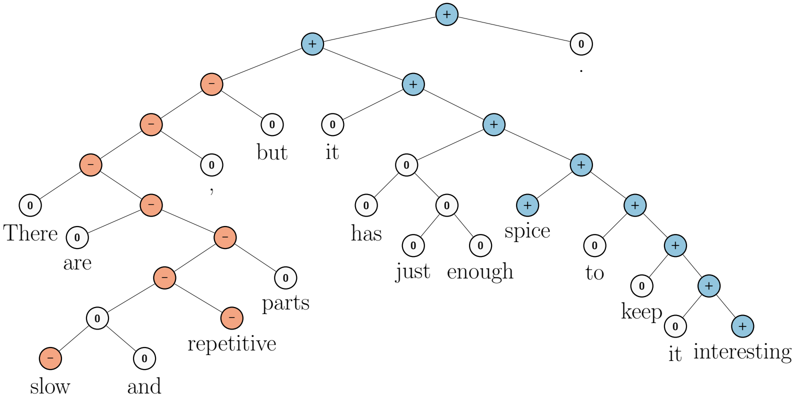

Monotonicity and semantic *precision*

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Kim smoked.	Kim didn't smoke.
↑	↓
Kim smoked cigars.	Kim didn't smoke cigars.

Monotonicity and semantic *precision*

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A student smoked.

↗ **A** Swedish student smoked.

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$\uparrow$ | $\downarrow$
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$\swarrow$ $\searrow$
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Most students smoked.
— $\nwarrow$
Most Swedish students smoked. | **Most** students smoked cigars.

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(Bowman 2016)

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Conclusions

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Recursive	Recursive	Recursive

Conclusions

Semantics	Semantic parsing	Deep learning
Recursive	Recursive	Recursive
Symbolic	Symbolic	Not symbolic

Conclusions

Semantics	**Semantic parsing**	**Deep learning**
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Compositional	Partly compositional	Compositional?

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Open-class lexicon often neglected	Learned symbolic lexicon	Learned lexical embedding

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Rich treatment of functional lexicon	Possible rich treatment of functional lexicon	No functional/open-class distinctions

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Thanks!

References I

Barker, Chris. 2007. Parasitic scope. *Linguistics and Philosophy* 30(4). 407–444.
Bolinger, Dwight. 1967. Adjectives in english: Attribution and predication. *Lingua* 18(1). 1–34.
Bowman, Samuel R. 2016. *Modeling natural language semantics in learned representations*. Stanford, CA: Stanford University dissertation.
Bumford, Dylan. 2017. Split-scope definites: Relative superlatives and Haddock descriptions. *Linguistics and Philosophy* 40(6). 549–593. doi:10.1007/s10988-017-9210-2.
Cooper, Robin. 2012. Book review: Computational semantics with functional programming Jan van Eijck and Christina Unger. *Computational Linguistics* 38(2). 447–449. doi:10.1162/COLI_r_00103.
Dever, Josh. 1999. Compositionality as methodology. *Linguistics and Philosophy* 22(3). 311–326. doi:10.1023/A:1005410301126.
Dowty, David. 2007. Compositionality as an empirical problem. In Chris Barker & Pauline Jacobson (eds.), *Direct compositionality*, 23–101. Oxford: Oxford University Press.
von Fintel, Kai. 1993. Exceptive constructions. *Natural Language Semantics* 1(2). 123–148.
Groenendijk, Jeroen & Martin Stokhof. 1991. Dynamic predicate logic. *Linguistics and Philosophy* 14(1). 39–100.
Haddock, Nicolas J. 1987. Incremental interpretation and combinatory categorial grammar. In *Proceedings of the 10th international joint conference on artificial intelligence*, 661–663.
Hall, Robert A., Jr. 1973. The transferred epithet in P. G. Wodehouse. *Linguistic Inquiry* 4(1). 92–94.
Higginbotham, James. 1986. Linguistic theory and davidson's program in semantics. In Ernest Lepore (ed.), *Truth and interpretation: Perspectives on the philosophy of Donald Davidson*, 29–48. Oxford: Basil Blackwell.
Hirst, Graeme. 1987. *Semantic interpretation and the resolution of ambiguity*. Cambridge: Cambridge University Press.
Hoeksema, Jacob. 1996. The semantics of exception phrases. In Jaap van der Does & Jan van Eijck (eds.), *Quantifiers, logic, and language*, 145–177. Stanford, CA: CSLI.
Horn, Laurence R. 2005. Diagnosing a diagnostic: Revisiting the quantifier constraint on exceptives. NYU Polarity Worskhop.
Janssen, Theo M. V. 1997. Compositionality. In Johan van Benthem & Alice ter Meulen (eds.), *Handbook of logic and language*, 417–473. Cambridge, MA and Amsterdam: MIT Press and North-Holland.
Kamp, Hans. 1981. A theory of truth and discourse representation. In Jeroen Groenendijk, Theo M. V. Janssen & Martin Stockhof (eds.), *Formal methods in the study of language*, 277–322. Amsterdam: Mathematical Centre.
Kazmi, Ali & Francis Jeffry Pelletier. 1998. Is compositionality formally vacuous? *Linguistics and Philosophy* 21(6). 629–633.
Keenan, Edward L. 1974. The functional principle: Generalizing the notion 'subject of'. In Michael W. La Galy, Robert A. Fox & Anthony Bruck (eds.), *Papers CLS 10*, 298–309. Chicago: Chicago Linguistic Society.
Levin, Beth, Lelia Glass & Dan Jurafsky. 2018. Systematicity in the semantics of noun compounds: The role of artifacts vs. natural kinds. *Linguistics* 57(3). 429–471. doi:10.1515/ling-2019-0013.
Liang, Percy, Michael I. Jordan & Dan Klein. 2013. Learning dependency-based compositional semantics. *Computational Linguistics* 39(2). 389–446. doi:10.1162/COLI_a_00127.

References II

Montague, Richard. 1970. Universal grammar. *Theoria* 36. 373–398. Reprinted in Montague (1974), 222–246.

Montague, Richard. 1974. *Formal philosophy: Selected papers of Richard Montague*. New Haven, CT: Yale University Press.

Nadathur, Prerna & Daniel Lassiter. 2014. Unless: An experimental approach. In *Proceedings of sinn und bedeutung 19*, Göttingen.

Partee, Barbara H. 1984. Compositionality. In Fred Landman & Frank Veltman (eds.), *Varieties of formal semantics*, 281–311. Dordrecht: Foris. Reprinted in Barbara H. Partee (2004) *Compositionality in formal semantics*, Oxford: Blackwell 153–181. Page references to the reprinting.

Partee, Barbara H. 1995. Lexical semantics and compositionality. In Lila R. Gleitman & Mark Liberman (eds.), *Invitation to cognitive science*, vol. 1, 311–360. Cambridge, MA: MIT Press.

Partee, Barbara H. 1996. The development of formal semantics in linguistic theory. In Shalom Lappin (ed.), *The handbook of contemporary semantic theory*, 11–38. Oxford: Blackwell.

Socher, Richard, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng & Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on Empirical Methods in Natural Language Processing*, 1631–1642. Stroudsburg, PA: Association for Computational Linguistics. `http://www.aclweb.org/anthology/D13-1170`.

Szabó, Zoltán Gendler. 2012. Compositionality. In Edward N. Zalta (ed.), *The Stanford encyclopedia of philosophy*, CSLI winter 2012 edn. `http://plato.stanford.edu/archives/win2012/entries/compositionality/`.

Warren, David H. D. & Fernando C. N. Pereira. 1982. An efficient easily adaptable system for interpreting natural language queries. *American Journal of Computational Linguistics* 8(3–4). 110–122.

Zadrozny, Wlodek. 1994. From compositional to systematic semantics. *Linguistics and Philosophy* 17(4). 329–342. doi:10.1007/BF00985572.