Compositionality or systematicity?

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Stanford Linguistics

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The Past, Present, and Future of Formal Semantics
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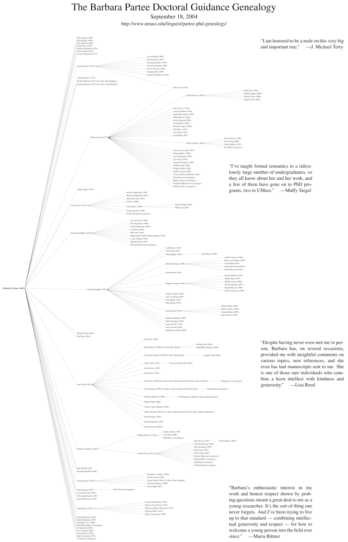
The thrill of scientific inquiry



Central questions

My central questions

When linguists seek compositional analyses of linguistic phenomena:

- What principles guide their investigations?
- What higher-level goals are they actually pursuing?

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. *Systematicity* might be a better goal.

Plan

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

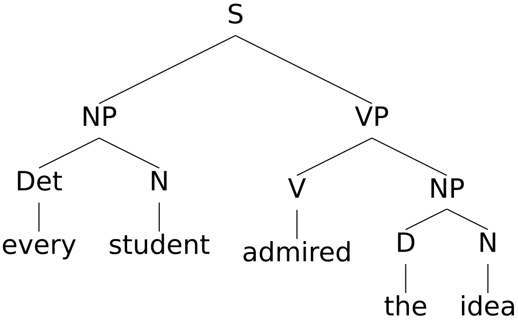
The compositionality principle

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

Informal statement

Compositionality

The meaning of a phrase is a function of the meanings of its immediate syntactic constituents and the way they are combined.

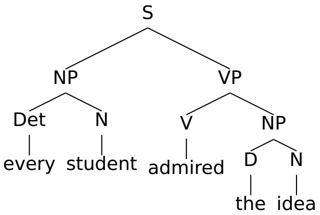


The usual motivation

1. Modeling all meaningful units

   $[\![every]\!] = \lambda f\ \lambda g\ \forall x\ ((f\ x) \rightarrow (g\ x))$

2. “Infinite” capacity
3. Creativity
4. Systematicity



Montague: Unconstrained compositionality

Partee (1996) on Montague (1970):

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.

[. . .]

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

Formal results

Zadrozny (1994)

Any meaning function (map from forms to meanings) can be turned into a compositional one in the sense of the homomorphism requirement.

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

Here is a non-compositional semantics:

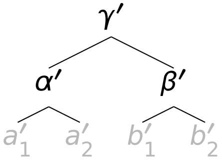
- $[\![\textit{sleep}]\!] = [\![\textit{doze}]\!]$
- $[\![\textit{sleep tight}]\!] \neq [\![\textit{doze tight}]\!]$

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

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).



The compositionality heuristic

Compositionality as methodology

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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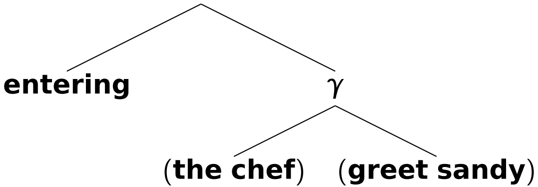
2. 

Example: Subjectless predicational adjuncts

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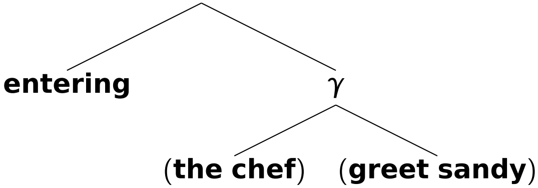
2. 

Potential rule

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

Example: Subjectless predicational adjuncts

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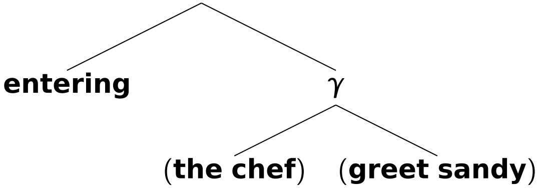
2. 

Potential rule

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

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.”

Example: Subjectless predicational adjuncts

Pragmatic constraint

The free variable in a subjectless predicational adjuncts should refer to a discourse topic.

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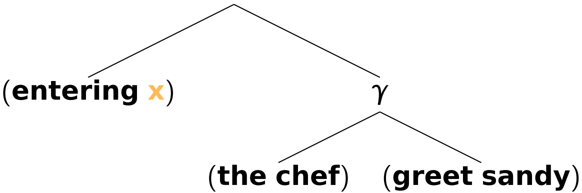
2. 

Example: Subjectless predicational adjuncts

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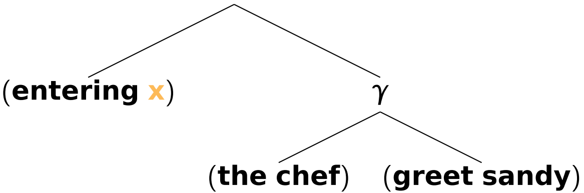

Subjects/topic correlation

In English, subjects are often topics.

Example: Compounds and systematicity

Partee (1995:341):

In compounds [. . .] there is no general rule for predicting the interpretation of the combination

Levin et al.'s (2019) novel compounds experiment:

Modifier	Head	Example	Event	Perceptual Environmental/
Artifact	Artifact	stew skillet	93%	7%
Natural kind	Artifact	stream wheel	88%	12%
Artifact	Natural kind	stew chickpea	66%	34%
Natural kind	Natural kind	stream vegetable	15%	85%

flat tire/beer/note/file

Semantic parsing

The semanticist's ideal

Every student attended a lecture

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

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

$$\lambda f\ \lambda g\ \forall z\ ((f\ z) \rightarrow (g\ z)) \quad \textbf{student}$$

$$\textbf{attended}_S \qquad \lambda g\ (\exists x\ (\textbf{lecture}\ x) \wedge (g\ x))$$

$$\lambda f\ \lambda g\ (\exists x\ (f\ x) \wedge (g\ x)) \quad \textbf{lecture}$$

The semanticist's ideal

Every student attended a lecture

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

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

$\lambda f\ \lambda g\ \forall z\ ((f\ z) \rightarrow (g\ z))$ **student**

$\textbf{attended}_l$ $\lambda g\ (\exists x\ (\textbf{lecture}\ x) \wedge (g\ x))$

$\lambda f\ \lambda g\ (\exists x\ (f\ x) \wedge (g\ x))$ **lecture**

The semanticist's ideal

Every child ate a lollipop

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

- $\lambda g\, \forall z\, ((\textbf{child}\ z) \rightarrow (g\ z))$
  - $\lambda f\, \lambda g\, \forall z\, ((f\ z) \rightarrow (g\ z))$
  - $\textbf{child}$
- $\lambda Q\, (Q\, (\lambda y\, (\exists x\, (\textbf{lollipop}\ x) \wedge (\textbf{ate}\ x\ y)))$
  - $\textbf{ate}_S$
  - $\lambda g\, (\exists x\, (\textbf{lollipop}\ x) \wedge (g\ x))$
    - $\lambda f\, \lambda g\, (\exists x\, (f\ x) \wedge (g\ x))$
    - $\textbf{lollipop}$

The semanticist's ideal

Every child ate a lollipop

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

$$\lambda g\ \forall z\ ((\textbf{child}\ z) \rightarrow (g\ z)) \qquad \lambda Q\ (\exists x\ (\textbf{lollipop}\ x) \land (Q\ (\lambda y\ (\textbf{ate}\ x\ y))))$$

$$\lambda f\ \lambda g\ \forall z\ ((f\ z) \rightarrow (g\ z)) \quad \textbf{child} \qquad \textbf{ate}_l \qquad \lambda g\ (\exists x\ (\textbf{lollipop}\ x) \land (g\ x))$$

$$\lambda f\ \lambda g\ (\exists x\ (f\ x) \land (g\ x)) \quad \textbf{lollipop}$$

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

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

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

But is this really so ideal?

Crude grammars refined via learning

Crude grammars refined via learning

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

Crude grammars refined via learning

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

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

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

Crude grammars refined via learning

N

dog : **dog**

V

dog : $\mathbf{dog}_V$

```
for w ∈ Words
    for X ∈ Categories
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```

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

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for $w \in \textit{Words}$
  for $X \in \textit{Categories}$
    for $d \in \textit{Domain}$
      yield '$X \to w : d$'

1	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**

Crude grammars refined via learning

for $w \in Words$
    for $X \in Categories$
        for $d \in Domain$
            yield ‘$X \rightarrow w : d$’

2	N	→	*dog*	:	**dog**
1	V	→	*dog*	:	**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 : **dog**$_v$

N
|
cat : **cat**

N
|
dog : **dog**

Crude grammars refined via learning

```
for w ∈ Words
    for X ∈ Categories
        for d ∈ Domain
            yield 'X → w : d'
```

3	N	$\rightarrow$	*dog*	:	**dog**
1	V	$\rightarrow$	*dog*	:	$\mathbf{dog}_{V}$
0	N	$\rightarrow$	*dog*	:	**cat**
1	N	$\rightarrow$	*cat*	:	**cat**
0	N	$\rightarrow$	*cat*	:	**dog**
0	V	$\rightarrow$	*jump*	:	**dog**
0	V	$\rightarrow$	*jump*	:	**jump**

N
|
dog : **dog**

N
|
dog : **dog**

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

N
|
cat : **cat**

N
|
dog : **dog**

Crude grammars refined via learning

```
for w ∈ Words
    for X ∈ Categories
        for d ∈ Domain
            yield 'X → w : d'
```

3	N	$\rightarrow$	*dog*	:	**dog**
1	V	$\rightarrow$	*dog*	:	$\mathbf{dog}_V$
0	N	$\rightarrow$	*dog*	:	**cat**
1	N	$\rightarrow$	*cat*	:	**cat**
0	N	$\rightarrow$	*cat*	:	**dog**
0	V	$\rightarrow$	*jump*	:	**dog**
1	V	$\rightarrow$	*jump*	:	**jump**

$$\begin{array}{c} \mathrm{N} \\ | \\ \textit{dog} : \textbf{dog} \end{array} \qquad \begin{array}{c} \mathrm{N} \\ | \\ \textit{dog} : \textbf{dog} \end{array}$$

$$\begin{array}{c} \mathrm{V} \\ | \\ \textit{dog} : \textbf{dog}_V \end{array} \qquad \begin{array}{c} \mathrm{V} \\ | \\ \textit{jump} : \textbf{jump} \end{array}$$

$$\begin{array}{c} \mathrm{N} \\ | \\ \textit{cat} : \textbf{cat} \end{array}$$

$$\begin{array}{c} \mathrm{N} \\ | \\ \textit{dog} : \textbf{dog} \end{array}$$

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0	N	$\rightarrow$	*dog*	:	**cat**
2	N	$\rightarrow$	*cat*	:	**cat**
0	N	$\rightarrow$	*cat*	:	**dog**
0	V	$\rightarrow$	*jump*	:	**dog**
1	V	$\rightarrow$	*jump*	:	**jump**

N | *dog* : **dog**   N | *dog* : **dog**

V | *dog* : $\mathbf{dog}_v$ V | *jump* : **jump**

N | *cat* : **cat**   N | *cat* : **cat**

N | *dog* : **dog**

Crude grammars refined via learning

```
for w ∈ Words
    for X ∈ Categories
        for d ∈ Domain
            yield 'X → w : d'
```

3	N	→	*dog*	:	**dog**
1	V	→	*dog*	:	**dog**$_v$
0	N	→	*dog*	:	**cat**
2	N	→	*cat*	:	**cat**
0	N	→	*cat*	:	**dog**
0	V	→	*jump*	:	**dog**
1	V	→	*jump*	:	**jump**

N — *dog* : **dog**   N — *dog* : **dog**

V — *dog* : **dog**$_v$ V — *jump* : **jump**

N — *cat* : **cat**   N — *cat* : **cat**

N — *dog* : **dog**

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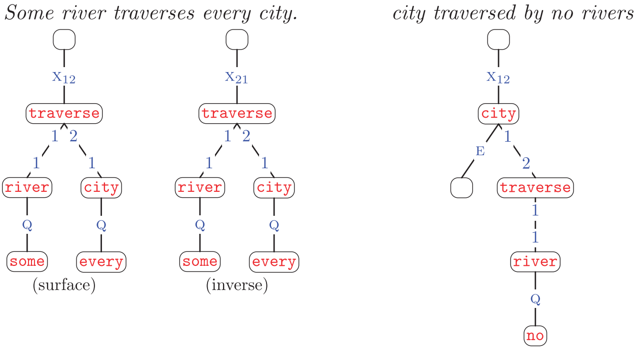
Crude grammars refined via learning

Liang et al. (2013):



(c) Quantifier scope ambiguity (Q, Q)

(d) Quantification (Q, E)

Additional feature functions

I previously showed some features that correspond to local trees. Those look nicely compositional. However, a smart NLPer will also have features like:

1. How many distinct lexical items are in the sentence?
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?

The linguist's ideal again

Every child ate a lollipop

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

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

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

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

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

Score: $+5$

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

Score: −2

Recursive deep learning models

Composition with functions or with vectors

Functions

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

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

$$[\![D]\!] \qquad [\![E]\!]$$

Vectors

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

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

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

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

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

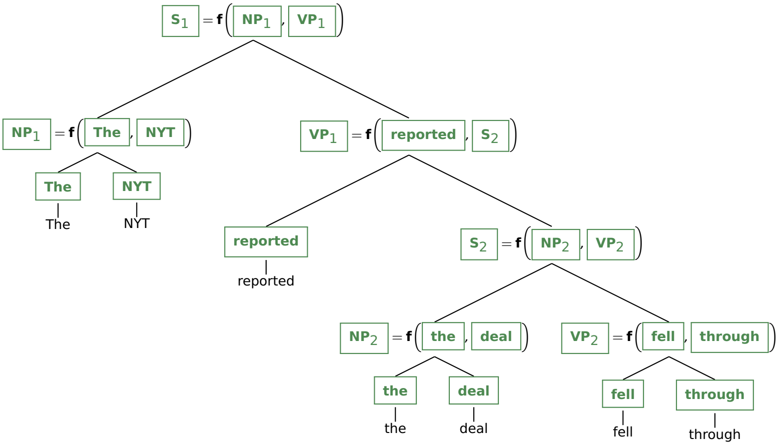
Simple example

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

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

not terrible

Recursive deep learning models



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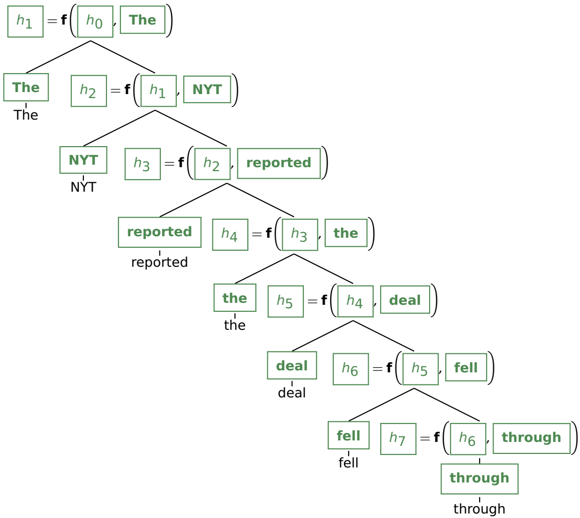
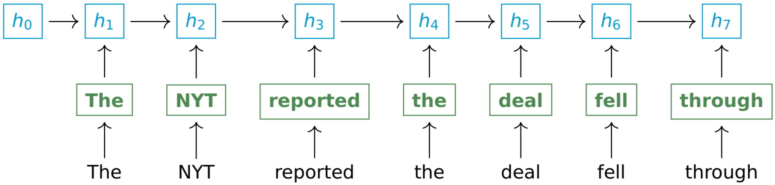
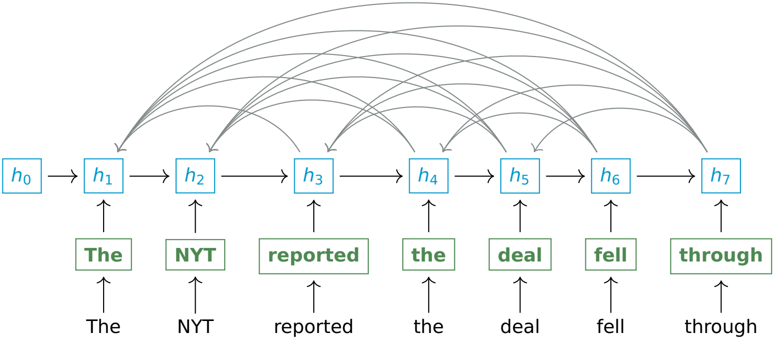


Recursive deep learning models



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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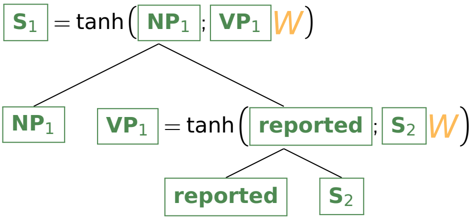
Global parameters creating local lexical effects



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

Global parameters creating local lexical effects

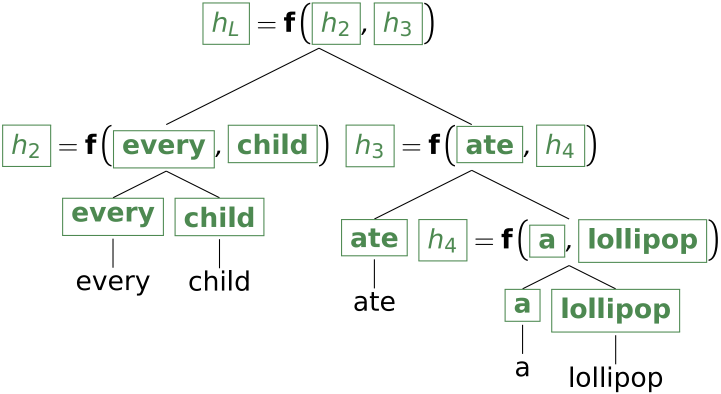
$$\tanh\left(\begin{bmatrix}-0.10 & 0.10 & -1.00 & 1.00\end{bmatrix}\begin{bmatrix}0.06 & 0.32\\ -0.14 & -0.53\\ 1.24 & 0.00\\ 0.02 & 1.06\end{bmatrix}\right) = \begin{bmatrix}-0.85 & 0.75\end{bmatrix}$$

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

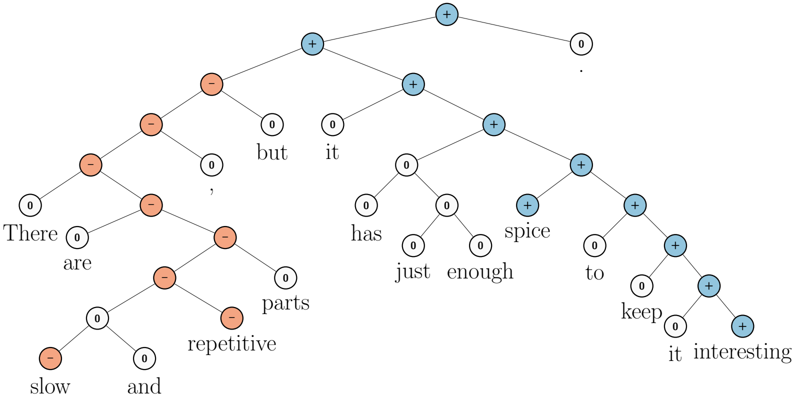
not terrible

The linguist's ideal again

Every child ate a lollipop



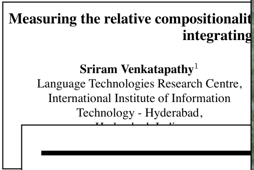
Examples from Socher et al. 2013



Conclusions

Semantics	Semantic parsing	Deep learning
Recursive	Recursive	Recursive
Symbolic	Symbolic	Not symbolic
Compositional	Partly compositional	Compositional?
Precise	Precise	Not precise
Purely representational	Preferences learned	Preferences learned
Open-class lexicon often neglected	Learned symbolic lexicon	Learned lexical embedding
Rich treatment of functional lexicon	Possible rich treatment of functional lexicon	No functional/open-class distinctions
Sharp sem/prag division	Blurry sem/prag division	No sem/prag division
Not at all scalable	Semi-scalable	Highly scalable
Deep analytic insights	Indirect analytic insights	Often opaque

Conclusions


Measuring the relative compositionalit
integrating

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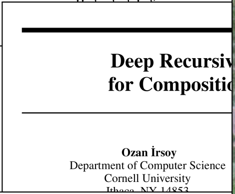
Deep Recursiv
for Compositio

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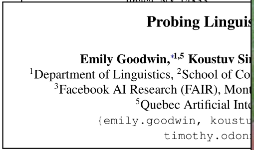
Probing Linguis

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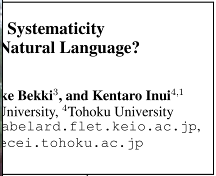
Systematicity
Natural Language?

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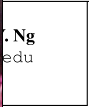
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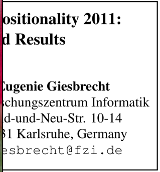
ositionality 2011:
d Results

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