Distributional semantics for linguists

Lecture 3a: Distributional semantics and composition

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Outline

- Overview
- Composing distributions: motivation
- Mitchell and Lapata (2010)
- 4 Baroni and Zamparelli (2010)
- 5 Coecke et al (2010)
- Issues
- Conclusion



Overview

- Composing distributions: the motivation. How to get from single words to phrases and sentences?
- Some compositional distributional models.
- Unanswered questions.

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Motivation

- Formal semantics gives an elaborate and elegant account of the productive and systematic nature of language.
- The formal account of compositionality relies on:
 - words (the minimal parts of language, with an assigned meaning)
 - syntax (the theory which explains how to make complex expressions out of words)
 - *semantics* (the theory which explains how meanings are combined in the process of particular syntactic compositions).

Motivation

- But formal semantics does not actually say anything about lexical semantics (the meaning of cat, cat', is the set of all cats in particular world).
- Distributions a potential solution?
- Also, if we make the approximation that distributions are 'meaning', then we need a way to account for compositionality in a distributional setting.

Why not just look at the distribution of phrases?

- The distribution of phrases even sentences can be obtained from corpora, but...
 - those distributions are very sparse;
 - observing them does not account for productivity in language.
- Some models assume that corpus-extracted phrasal distributions are irrelevant data.
- Some models assume that, given enough data, corpus-extracted phrasal distributions have the status of gold standard.

Some distributional compositionality models

- Mitchell and Lapata (2010): word-based model, task-evaluated.
- Baroni and Zamparelli (2010): word-based, evaluated against phrasal distributions.
- Coecke, Sadrzadeh and Clark (2011): CCG-based model, task-evaluated.

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The model

- Word-based (5 words on either side of the lexical item under consideration).
- The composition of two vectors \vec{u} and \vec{v} is some function $f(\vec{u}, \vec{v})$. M & L try:
 - addition $p_i = \vec{u_i} + \vec{v_i}$
 - multiplication $p_i = \vec{u_i} \cdot \vec{v_i}$
 - tensor product $p_{ij} = \vec{u_i} \cdot \vec{v_i}$
 - circular convolution $p_{ij} = \sigma_j \vec{u_j} \cdot \vec{v_{i-j}}$
 - ... etc
- Task-based evaluation: similarity ratings. Multiplication is best measure.



Example

early i

africa::9.75873 african::6.87337 aftermath::3.40748 afternoon::42.2096 afterwards::7.46585 again::9.00563 age::15.6464 aged::5.99896 agencies::4.91747 agency::7.28471 agent::4.63014 agents::4.21793 ages::45.003 ago::18.8909 agree::5.05183 agreed::6.36066 agreement::7.64836

age n

africa::3.56225 african::1.88733 aftermath::1.37812 afternoon::1.9041 afterwards::3.86807 again::2.78339 age::0 aged::24.6173 agencies::1.57129 agency::3.13776 agent::2.24935 agents::1.68319 ages::0 ago::19.2306

agree::3.67157

agreed::2.61272

agreement::0.912126

agricultural::2.66057

early jage n

africa::34 76303 african::12.97231 aftermath::4.69591 afternoon::80.3712 afterwards::28.87843 again::25.06618

age::0 aged::147.67819 agencies::7.72677 agency::22.85767 agent::10.41480 agents::7.09957

ages::0

ago::363.2833 agree::18.54814 agreed::16.61862 agreement::6.976268

agricultural::30.26265

agricultural::11.3745

Difference in top-rated contexts for early age

multiplication 1990s 1980s 1970s 20th 1960s childhood 1950s age 1940s 1920s 1930s 19th late century morning stages settlers

phrase talent interested showed learned piano studying exposed ages parents encouraged singing educated interest uncle violin baronet eldest

warning

raised

12/37

Discussion: the meaning of f

- How do we interpret $f(\vec{u}, \vec{v})$ linguistically?
- Intersection in formal semantics has a clear interpretation:
 ∃x[cat'(x) ∧ black'(x)]
 There is a cat in the set of all cats which is also in the set of black things.
- But what with addition, multiplication (let alone circular convolution)??

Addition

- Addition is not intersective: the whole meaning of both \vec{u} and \vec{v} are included in the resulting phrase.
- No sense disambiguation and no indication as to how an adjective, for instance, modifies a particular noun (i.e. the distributions of red car and red cheek both include high weights on the blush dimension).
- Too much information

Multiplication

- Multiplication is intersective.
- But it is commutative in a word-based model:

The cat chases the mouse = The mouse chases the cat.



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Overview

- Word-based model for adjective-noun composition.
- Composition is the multiplication of vectors/matrices learned from phrasal distributions.
- 'Internal' evaluation: composition is evaluated against phrasal distributions.

Assumptions

- Given enough data, distributions for phrases should be obtained in the same way as for single words.
- There is no single composition operation for adjectives. Each adjective acts on nouns in a different way.

Adjective types, Partee (1995)

- Intersective: carnivorous mammal
 ||carnivorous mammal|| = ||carnivorous|| ∩ ||mammal|
- Subsective: skilful surgeon
 ||skilful surgeon|| ⊆ ||surgeon||
- Non-subsective: former senator
 ||former senator|| ≠ ||former|| ∩ ||senator||
 ||former senator|| ⊈ ||senator||

System

- For each adjective, a matrix is learned from actual AN phrases using partial least squares regression.
- Test by measuring distance between a given adjective-noun combination and the corresponding phrasal distribution.

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Overview

- Based on pregroup grammar.
- Composition involves tensor product and point-wise multiplication.
- Evaluated on similarity task.

Thanks to Steve Clark for some of the slides!

Pregroup grammar

A pregroup is a partially ordered monoid in which each element a
has a left adjoint a^l and a right adjoint a^r such that

$$a' \cdot a \rightarrow 1$$
, $a \cdot a^r \rightarrow 1$

The monoid is the set of grammatical types (NP, NP^r, NP^l, NP^{rr}, NP^{ll}, S, PP, ...) with the juxtaposition operator (·) used to derive complex types and the empty string as unit (1)

$$NP \cdot (NP^r \cdot S \cdot NP^l) \cdot NP$$



Categorial Grammar Derivation

$$\frac{Google}{NP} \quad \frac{bought}{NP \setminus S/NP} \quad \frac{Microsoft}{NP}$$



Categorial Grammar Derivation

$$\frac{Google}{NP} \quad \frac{bought}{NP \backslash S/NP} \quad \frac{Microsoft}{NP} \\ \hline \\ NP \backslash S \\ >$$

Categorial Grammar Derivation

$$\begin{array}{c|c} Google & bought & Microsoft \\ \hline NP & NP \backslash S / NP & \hline NP \\ \hline & & \hline NP \backslash S \\ \hline & & S \\ \end{array} >$$



Pregroup Derivation

$$\frac{Google}{NP} \quad \frac{bought}{NP^r \cdot S \cdot NP^l} \quad \frac{Microsoft}{NP}$$

Pregroup Derivation

$$\frac{Google}{NP} \underbrace{\begin{array}{c} bought \\ NP^r \cdot S \cdot NP^l \end{array}}_{NP^r \cdot S} \underbrace{\begin{array}{c} Microsoft \\ NP \end{array}}_{NP}$$

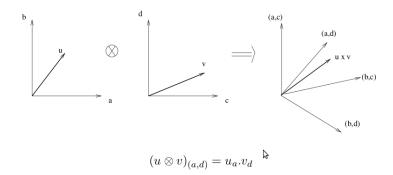
Pregroup Derivation

Various semantics spaces

 Lexical items of various grammatical types live in different 'spaces'.

- Representations can be vectors or matrices.
 e.g. a transitive verb may be a matrix represented in a tensor product space N ⊗ S ⊗ N.
- Basic types like nouns are vectors with components equal to TF*IDF values.
- Composition involves point-wise multiplication.

The tensor product



The sentence space

- What is the sentence space?
- Truth-theoretic interpretation: sentence space has two dimensions, True and False.
- Distributional interpretation: a point in the distributional space used for verbs. But what does this really mean (in particular in the case of complex sentences)??

Truth in a 2-dimensional space

dog chases cat

 $0.8.0.8.0.9 + 0.75.0.8.0.6 + 0.2.0.8.0.0 + 0.1.0.1.0.0 + \dots$

Sentence meaning in a multi-dimensional space

dog chases cat

	(fluffy,fluffy)	$\langle fluffy, fast \rangle$	3,0.6 0.8,0.0 0.1,\$0 0.1,0.5 0.5,0.0 0.0,0.0				
chases	0.8	0.75	0.2	0.1	0.2	0.2	0.0
dog,cat	0.8,0.9	0.8,0.6	0.8,0.0	0.1,6.0	0.1,0.5	0.5,0.0	0.0,0.0
\overrightarrow{dog} chases cat	0.576	0.36	0.0	0.0	0.01	0.0	0.0

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The meaning of the sentence

- In formal semantics, meaning is denotational and truth-theoretic.
- Kim sleeps is true iff Kim is in the set of sleeping things.
- Distributions are more about intension than extension, so should we talk of truth?
- If not, what should the meaning of a sentence be?



Beyond intersection

- What about non-intersective composition? (fake, small, alleged...)
- Even the semantics of intersective phrases is more than the intersection of their parts.

Is intersection enough?

A big city: just a city which is big? See loud, underground, advertisement, crowd, Phantom of the Opera...



What should we compose?

one has the common intuition that there is a perceived difference between [...] "Indian elephant" and "friendly elephant". [...] an Indian elephant is one of a recognized variety of elephants, and their properties are not simply those of being an elephant, and being from India, but something more (such as disposition, size of ears, etc. etc.) – it's a (sub)species. In this sense, "Indian elephant" differs from "friendly elephant" because a friendly elephant is no more than an elephant that is friendly, and that's it.

Carlson (2010)

 What is the best representation for *Indian elephant*? The phrase or the composed form? Or both? (But how to do both??)



Logical operators

- Treatment of logical operators is unclear.
- In formal semantics, a quantifier 'counts' over the elements of a set.

$$Q(x)[rstr(x) \land scp(x)]$$

$$\exists (x)[cat'(x) \land run'(x)]$$

No set in distributional semantics...



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Conclusion

- We need a way to integrate lexical and compositional semantics.
- General feeling is that the composition of distributions should produce another distribution which expresses the meaning of a phrase/sentence.
- How to do this is only clear for certain constructions.
- What is the distribution of a sentence?

